Research paper

Detection of Induced Damage in Medium-Density Fiberboard Panels Using a Neural Network Method

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【Summary】

This research assessed the feasibility of using a neural network to detect induced and interior damage to small samples of medium-density fiberboard (MDF). The neural network was a 3-layer back-propagation network. The undamaged stress wave frequency spectrum patterns were used to train the neural network. In a previous study, we successfully used the trained patterns to evaluate low levels of damage in samples of MDF onto which various percentages of their estimated failure loads were applied. In this experiment, after introduction of grooves on the surface or a hole through the center of the samples, a small change in the wave patterns occurred. The neural network has the unique ability to train itself using data to recognize spectral patterns and was successfully used to detect structural damage.

Key words: neural network, back-propagation neural network, medium-density fiberboard, stress waves.

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研究報告

利用類神經網路辨識中密度纖維板加工後之非破壞頻譜變化

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摘　要

本研究針對類神經網路使用來偵測中密度纖維板結構低破壞程度之可行性評估。類神經網路是一種計算系統，它使用大量簡單的相連人工神經元來模仿生物神經網路的學習能力，其中又以由三層網路所連結之倒傳遞類神經網路(back-propagation neural network)最為被普遍應用在診斷、預測功能上。先前研究已成功的辨識出中密度纖維板在其彈性限度內受不同載重後，因其結構受力後所導致應力波頻譜之變化，延續此研究成果利用此頻譜來訓練倒傳遞類神網路，以非破壞應力波量測試中密度纖維板當受不同人為加工後(如表面開槽、中間層開孔等)的結構破壞程度之頻譜，經過學習之類神經網路，可以成功地偵測。

關鍵詞：類神經網路、倒傳遞類神經網路、中密度纖維板、應力波。

龍暐、Robert W. Rice。2009。利用類神經網路辨識中密度纖維板加工後之非破壞頻譜變化。台灣林業科學24(1):51-60。

INTRODUCTION

Many researchers have investigated nondestructive testing (NDT) to evaluate the mechanical properties of wood and wood-based composite materials. The most common methods assess the relationship between mechanical properties and a stress wave velocity using a regression analysis (Ross and Pellerin 1991). However, these methods have limited use in composite board manufacturing plants because regression analysis does not adapt well to the changing environment of manufacturing plants. Regression analysis also requires specification of a functional model and evaluation of the statistical significance of the model's parameters with new data. An effective, reliable, nondestructive, damage assessment methodology would be a valuable tool for evaluating wood-based composites that have undergone or are undergoing stress.

A number of researchers have utilized stress wave propagation as a nondestructive testing tool for wood and wood-based composites (Shaler 1982, Ross 1984). Stress wave propagation in wood and wood-based composites depends on the (1) density, (2) moisture content, (3) geometry, (4) boundary conditions, and (5) impact forces. A stress wave induced by an impactor hitting a specimen that is composed of an isotropic, homogeneous, and elastic material is represented in Fig. 1.

The observed wave behavior can be modeled using a 1-dimensional stress wave equation as follows:

$$\frac{\partial^2 u}{\partial t^2} = C^2 \frac{\partial^2 u}{\partial x^2} \quad (1)$$

where μ is the longitudinal particle displacement of a cross-section of the bar at x and C is the speed of the wave propagating in the bar.

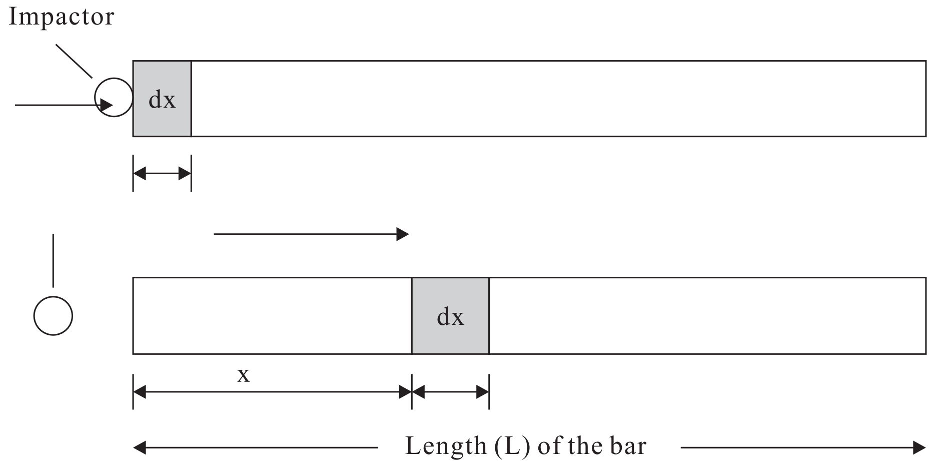

Fig. 1. Propagation of a stress wave in a bar.

The relationship between the dynamic modulus of elasticity (E_d) and stress wave velocity (C) is given by,

$$E_d = C^2\rho/g \quad (2)$$

where C is the speed as the wave propagates in the bar, ρ is the density, g is the acceleration due to gravity.

Many investigators have developed neural networks (Lippmann 1987). Neural networks have the unique ability to be trained to recognize spectral patterns and have been used with success to detect structural damage (Wu et al. 1992, Shin and Park 2000). Wu et al. (1992) and Elkordy et al. (1993) used a neural network for damage diagnosis in composite materials. The back-propagation network is one of the most successful recurrent network paradigms in use today (Huang and Zhang 1994, Tarng et al. 1994). Our previous study successfully used a back-propagation neural network to evaluate low levels of damage in samples of medium-density fiberboard (MDF) (Long and Rice 2008). Following a feasibility study, the trained network was utilized to discriminate damaged samples from an artificially created groove or hole through its cross-section. The measurement error between the damaged and undamaged samples was assessed to determine the effects of the applied damage types.

The basic hypothesis for this research was that no damage should exist in samples. As such, the neural network could be trained based on patterns of samples having no load history. Furthermore, samples had no visual or mechanical damage. The "measurement error" used to test the basic hypothesis was defined as follows:

$$\varepsilon = (\frac{1}{2}) \sum_j (T_j - Y_j)^2 \quad (3)$$

where ε is the measurement error, T_j is the desired output, and Y_j is the actual output.

The purpose of this study was to determine the feasibility of using neural networks to detect intentionally induced damage in small samples of MDF. The specific objectives were as follows:

1. To establish a reference pattern obtained when no load history (undamaged) MDF samples were used to train a neural network; and
2. To compare variations obtained when a neural network pattern developed from undamaged MDF samples was compared to the frequency spectra of stress waves taken from "damaged" samples to which artificial

damage as a groove or a hole through its cross-section had been applied.

MATERIALS AND METHODS

Preparation of MDF specimens

The primary experiments consisted of preparing 20 samples of 2 thicknesses of 1.25 and 1.9 cm (1/2 and 3/4 inch) of MDF (Georgia-Pacific, Old Town, ME, USA). There was no apparent visual damage to any samples. Samples were cut parallel to the machine direction that was according to the sandmarks and were cut into samples measuring 7.6 cm wide by 22.9 cm long. After the samples were cut, they were conditioned at 21℃ and 65% relative humidity (5.1% equilibrium moisture content, EMC).

A schematic of the experimental setup and measuring instrumentation is shown in Fig. 2. The impact damper system and receiving transducer were connected to an amplifier (Brüel and Kjær type 2635, Denmark), dynamic signal analyzer (HP 35665A, USA), and a microcomputer. The system consisted of an impact device for generating stress waves, a transducer, and a charge amplifier which captured and analyzed the stress waves. Fast Fourier transformation (FFT) was used to capture a pulse and compute the frequency spectrum. The information was then transferred to a microcomputer for analysis. The data were collected for a frequency range of 0~6.4 kHz using 800 lines of resolution in the frequency domain corresponding to 8 Hz of frequency resolution. The transferred signal dataset was then processed for neural network training and testing.

The basic experimental method consisted of 3 steps. First, frequency spectra were calculated from stress waves which had passed through samples of undamaged MDF (Fig. 3). Second, the frequency spectra of waves from the undamaged MDF were used to train a feed-forward back-propagation neural network to recognize a “good” spectral pattern. Third, the difference or “error” derived from a comparison of the neural network pattern and frequency spectra taken from samples with 2 types of damage were statistically compared to determine if the differences could be related to the damage types.

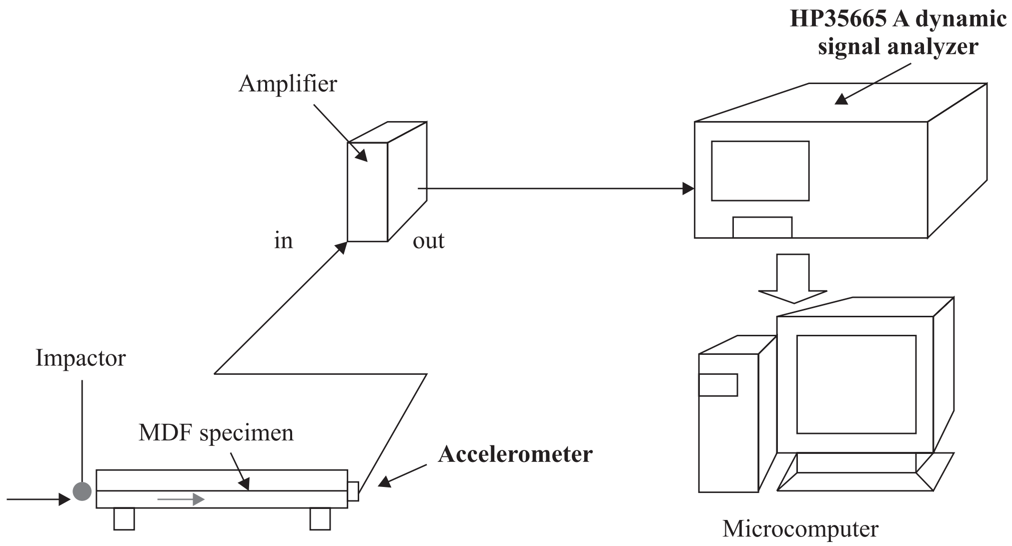

Fig. 2. Schematic of the stress wave-measuring system.

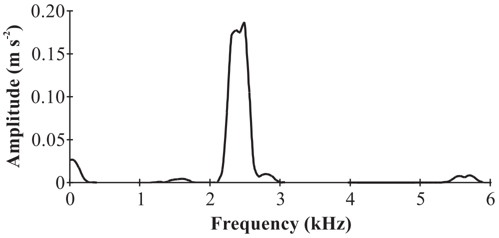

Fig. 3. Frequency spectra calculated from stress waves passing through samples of undamaged medium-density fiberboard (0~6 kHz).

Effect of induced and interior damage

Ten samples were prepared for each thickness of MDF (7.6 by 22.9 by 1.25/1.9 cm thick). The stress wave and frequency spectra were determined in undamaged samples before cutting the grooves or drilling a hole. Two grooves measuring 0.16 cm deep were cut into 5 specimens at the center on the surface of both sides to reduce their cross-section and affect wave propagation (Fig. 4). Five additional specimens were prepared by drilling a hole, 0.95 cm in diameter, through the center (Fig. 5).

After training, the frequency spectra from the damaged samples were compared to the trained neural network pattern. The data were used to see how well the trained network could discern and discriminate samples before and after damage.

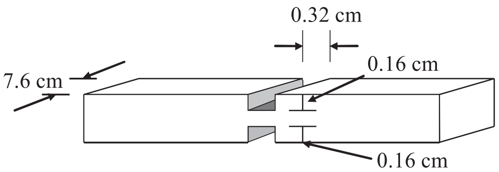

Fig. 4. Sample with a reduced cross-section caused by grooving.

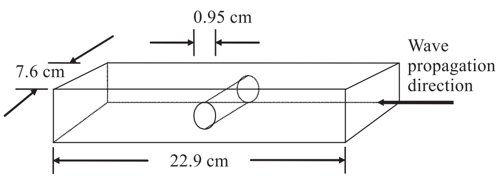

Fig. 5. Sample with a hole through its cross-section.

A previous study (Long and Rice 2008) successfully built a knowledge base with the neural network by: (1) collecting the frequency spectra of the stress wave patterns for training and testing; (2) training the neural network with the an array containing a large number of the undamaged frequency spectra; (3) verifying the trained network by comparing a single wave taken from each of 20 undamaged samples with the trained neural network pattern; and (4) determining the difference or "error" between the undamaged neural network pattern and frequency spectra from damaged samples.

The back-propagation learning algorithm was used to train the neural network and establish the interconnection weights (Fig. 6). Weights of the network that are generally randomly set were initialized to begin the training. The neural network was trained using the frequency spectra of undamaged samples. After the training process, the frequency spectra from damaged specimens were compared to the trained neural network pattern. These data were used to see how well the learned neural network could discern and discriminate between damaged and undamaged samples.

Sensitive vibration measurements are subject to variation from a number of sources. Therefore, it is important to recognize and eliminate extreme values that are not valid representations of the material/material analysis system. A 95% level of statistical significance was selected to define which factors had an effect on the dependent variables. Therefore, differences of damaged types were termed significant if a significant difference (p value < 0.05) was found. An analysis of variance (ANOVA) was conducted to compare the measurement error of the 2 types of

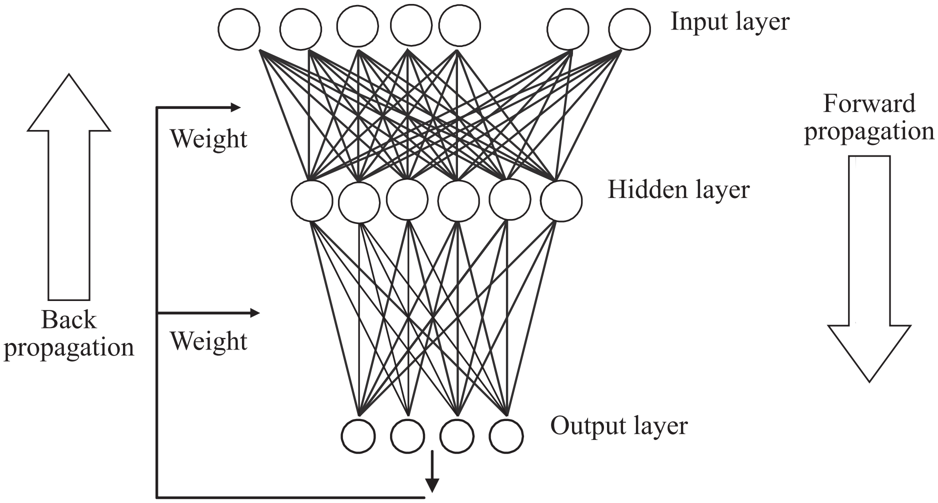

Fig. 6. Schematic diagram of a 3-layer feed-forward back-propagation neural network.

damage. Two-way ANOVA, general linear model (GLM), and multiple contrast tests were used to analyze the results. The procedure was used to analyze the variance to evaluate possible differences and interactions between each property of the damage types, sample variance, and replicates.

RESULTS AND DISCUSSION

The back-propagation neural network for determining undamaged and damaged levels of MDF was trained to utilize the undamaged stress wave patterns from each thickness of specimens. A training dataset consisting of 20 undamaged stress wave patterns of the process operating conditions was constructed for each thickness of MDF. Damage was detected by the neural network and compared to the learned wave pattern; this was used to indicate damage to the MDF.

The major objectives considered here were the detection accuracy and how the sensitivity of the detection varied with stress wave patterns due to the damage types. A training process presents the network with undamaged wave patterns and self-organizes so that it correctly recognizes the undamaged wave pattern. When trained successfully, differences were not very obvious between undamaged wave patterns. This means that differences between undamaged wave patterns were smaller than those of damaged wave patterns. In an earlier study, we were successful in using the neural network to diagnose the extent of individual damage from the frequency spectrum of a damaged structure (Long and Rice 2008). These observations are currently being used to investigate structural damage detection.

Velocity of stress wave transmission

How long a stress wave propagated in the MDF specimen was computed by equation (4):

$$C = \frac{2\lambda}{t} \tag{4}$$

where λ is the length of the specimen (cm) and t is the time of a period of stress wave (s). The results of the time of the stress wave period was computed for 1.25- and 1.9-cm (1/2- and 3/4-in.)-thick MDF. Using ANOVA and Tukey's studentized range (HSD) tests, average times of specimens of the same thickness showed no significant differences. This means that the average stress wave period was relatively consistent regardless of the number of specimens measured. There was also no significant difference between the 1.25- and 1.9-cm-thick specimens (Table 1).

Effect of induced and interior damage

Figure 7 shows the stress waves and their associated frequency spectra after cutting a groove in 2 surfaces of a sample. The magnitude of the dominant frequency from the grooved samples was lower than that of

Table 1. Analysis of speed variations among 2 thicknesses of medium-density fiberboard samples ($cm\ s^{-1}$)[1)]

Thickness (cm)	Number	Mean	Std. deviation	Tukey grouping
1.25	10	125005.6	872.9	A
1.9	10	124688.1	445.3	A

Mean, average speed of the stress wave ($cm\ s^{-1}$).

F value = 1.62, $p = 0.24 > 0.05$, ANOVA not significant.

Means with the same letter do not significantly differ.

1) Velocity (C) of the stress wave ($cm\ s^{-1}$), $C = \frac{2\lambda}{t}$ (4), where λ is the length of the specimen (cm) and t is the period of stress wave (s).

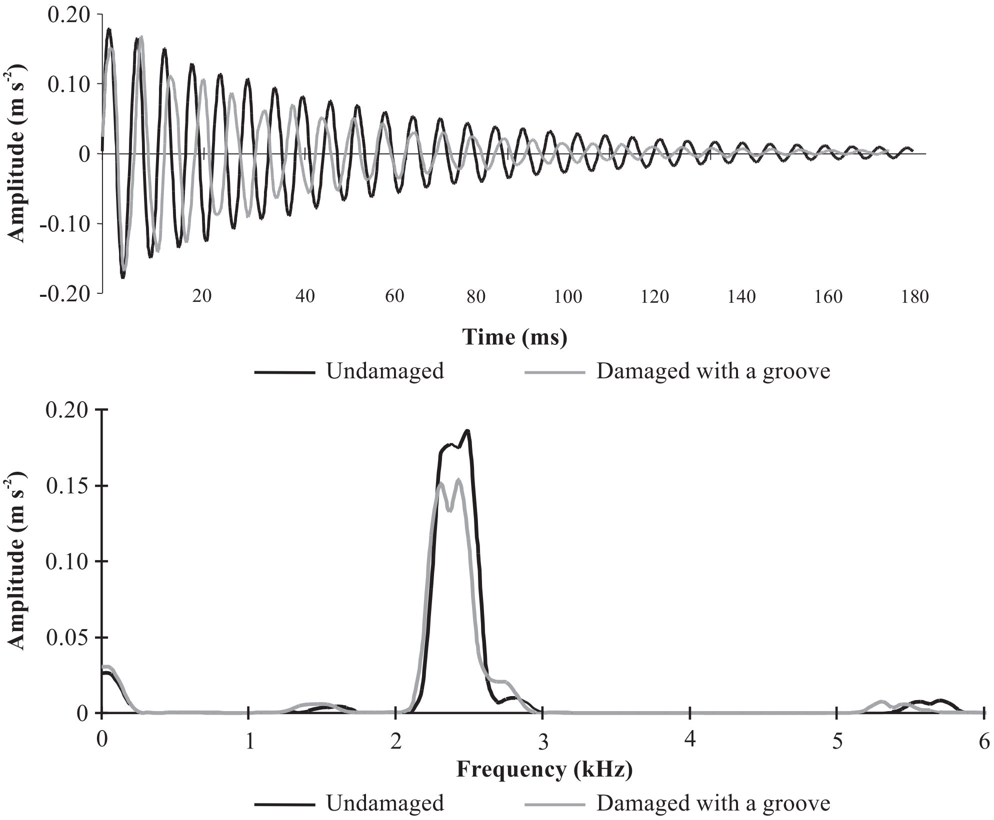

Fig. 7. (a) Typical stress waves and (b) associated frequency spectra before (undamaged) and after cutting surface grooves (damaged with a groove) (1.25-cm-thick sample).

samples without the groove. This means that there was some energy loss when the stress wave passed around the groove. There was a relationship between the groove and the magnitude of the amplitude at the maximum peak.

The neural network was trained using undamaged samples and the pattern learned was compared to the frequency spectra from the grooved samples. The results are shown in Fig. 8 and Table 2.

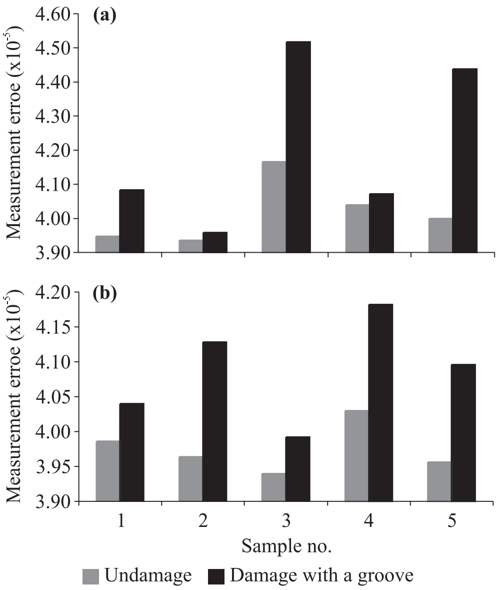

Fig. 8. Average measurement errors of undamaged neural network patterns of various samples damaged with a groove of (a) 1.25- and (b) 1.9-cm-thick samples.

It is evident from the measurement error of specimens with the groove that the error significantly increased. In most cases, the observed differences were related to a drop in the magnitude of the peak. The drop was probably due to the energy loss of the stress wave as a result of the groove.

Figures 9 and 10 represent the stress waves and their frequency spectra before and after drilling a hole in the MDF samples. For 1.25-cm-thick specimens, Fig. 9 shows that the amplitude of the frequency spectrum for samples with the hole was larger than that of samples without the hole. This indicates that there was less energy loss than when the stress wave passed through a sample with a hole, because the wave was forced to concentrate and pass through the surface layers that have higher density than the middle layer. In addition, the hole/thickness ratio is also important in wave energy transfer.

For 1.9-cm-thick samples, Fig. 10 shows the amplitude of the frequency spectrum for a typical sample with a hole through its center. A slight decrease was expected because of the energy loss of the stress wave due to the hole. However, the 1.9-cm-thick samples were less affected than were the 1.25-cm-thick samples because less of the section surface material was removed.

Figure 11 shows the measurement error obtained when the neural network pattern

Table 2. Analysis of measurement errors before and after cutting a groove in medium-density fiberboard samples

Thickness (cm)		Number	Mean	Std. deviation	Tukey grouping
1.25	Before cutting the groove	25	4.06×10^{-5}	1.24×10^{-6}	A
p = 1.0E-4	After cutting the groove	25	4.21×10^{-5}	2.28×10^{-6}	B
1.9	Before cutting the groove	25	3.98×10^{-5}	3.44×10^{-7}	A
p = 1.0E-4	After cutting the groove	25	4.09×10^{-5}	6.85×10^{-7}	B

Alpha = 0.05.
Means with the same letter do not significantly differ.

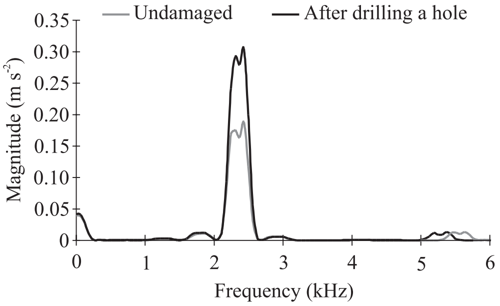

Fig. 9. Typical stress wave frequency spectra before and after drilling a hole (1.25-cm-thick sample).

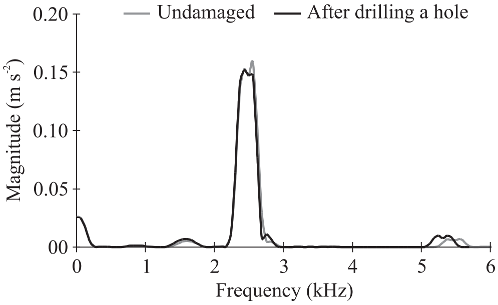

Fig. 10. Typical stress wave frequency spectra before and after drilling a hole (1.9-cm-thick sample).

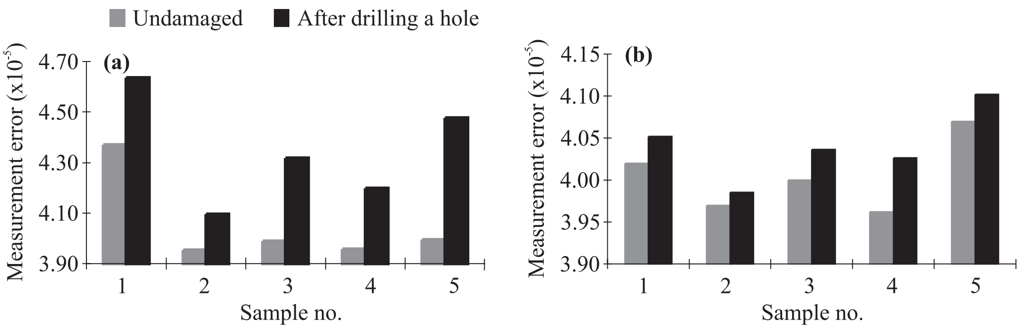

Fig. 11. Average measurement errors of undamaged neural network patterns of various samples damaged with a hole of (a) 1.25- and (b) 1.9-cm-thick sample.

Table 3. Analysis of measurement errors before and after drilling a hole in medium-density fiberboard samples

Thickness (cm)		Number	Mean	Std. deviation	Tukey grouping
1.25	Before drilling the hole	25	4.05×10^{-5}	2.00×10^{-6}	A
p-value = 1.0E-4	After drilling the hole	25	4.35×10^{-5}	1.63×10^{-6}	B
1.9	Before drilling the hole	25	4.00×10^{-5}	3.95×10^{-6}	A
p-value = 1.0E-4	After drilling the hole	25	4.04×10^{-5}	3.99×10^{-6}	B

Alpha = 0.05.
Means with the same letter do not significantly differ.

obtained from undamaged samples was compared to the stress waves from samples with a hole. Each bar is the average measurement error from 5 replicates. These results were statistically compared, and the results are shown in Table 3. It is evident that the measurement error of the peak magnitude of undamaged sample frequency spectra was lower than that of samples containing a hole.

CONCLUSIONS

The feasibility of using a neural network to detect the structural damage in MDF was explored using a feed-forward back-propagation neural network. The network not only recognized the undamaged frequency patterns, but usually indicated the pattern variation in the frequency spectra as damaged types.

The neural network was trained to recognize undamaged samples and those with grooves in the surface or a hole through the center of the sample. The results of the experiments are very encouraging. The research provides the following advantages.

1. The neural network can be trained with a limited number of frequency spectra.
2. The learned neural network can also detect changes in the frequency spectra due to cutting a groove and drilling a hole in the MDF samples.

The feed-forward back-propagation neural network is one of the first types of networks developed and has been the most widely applied network to date. These observations are currently being investigated for detection of damaged structures.

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