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Towards an optimization of automatic defect detection by artificial neural network using Lamb waves

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ABSTRACT

This paper presents a damage detection method based on the inverse pattern recognition technique by artificial neural network (ANN) using ultrasonic waves. Lamb waves are guided elastic waves, are widely employed in nondestructive testing thanks to their attractive properties such as their sensitivity to the small defects. In this work, finite element method was conducted by Abaqus to study Lamb modes propagation. A data collection is performed by the signals recorded from the sensor of 300 models: healthy and damaged plates excited by a tone burst signal with the frequencies: 100 kHz, 125 kHz, 150 kHz, 175 kHz, 200 kHz, and 225 kHz. The captured signals in undamaged plat are the baseline, whereas the signals measured in damaged plates are recorded for various positions of external rectangular defects. To reduce the amount of training data, only two peaks of measured signals are required to be the input of the model. Continuous wavelet transform (CWT) was adopted to calculate the key features of the signal in the time domain. The feed forward neural network is implemented using MATLAB program. The data are divided as follows: 70% for training the model, 25% for the validation, and 5% for the test. The proposed model is accurate estimating the position of the defect with an accuracy of 99.98%.

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1. INTRODUCTION

The mechanical parts are often subjected to many constraints and deformation leading to the appearance of external defect. This causes the weaknesses or their fracture. Therefore, many nondestructive testing methods are developed to predict the defect even before the first stage. One of the most used methods is Lamb waves. These waves are sensitive to small defect. They are used to control the corrosion of pipe [1] welding defect [2] in isotropic plate [3] or in composite cylinders [4].

One of the challenging tasks is to choose the adequate mode and the corresponding signals. Lamb waves consisted of propagating of fundamentals modes: antisymmetric noted A_0 and S_0. When the signal interacts with the defect, the propagating mode may convert to the other mode. This variation of the nature can noise the post processing and induce error detection. So many authors have studied the conversion phenomenon like [5], [6].

Post processing is a crucial step where the characteristics of captured signals are calculated. Among many, continuous wavelet transform (CWT) is most used in the field of nondestructive testing. It allows the analysis of time-frequency information, extracts and separates out frequency information from a timeseries.

The CWT allows knowing the time when the signal reaches the extreme magnitude, this time is a key feature of the signal in the time domain which dominates signal's description. Boashash [7] introduced the time-frequency analysis. Su and Ye [8] has applied CWT to extract the characteristic and data compression. Walenczykowska and Kawalec [9] has proposed an algorithm based on CWT for the automatic recognition of selected radar signals.

Two principal's transducer configurations are used to measure the damage: pulse echo and pitch catch. In the first technic, the actuator at the same time is the sensor placed before the defect, however, in the second technic, the actuator is placed before the defect, while the sensor is placed after the defect. Two technics are used, but pulse echo is most suitable to precisely detect the location of the crack as reported in [10]–[13].

SHM is structural health monitoring that enables the control in situ the integrity of the parts and allows rapid intervention. In this fields, many researchers have developed a lot of methods aiming to evaluate and estimate the defect geometry and position. These methods are divided into three categories: numerical, analytical, and experimental. Recently and with the development of machine learning (ML) algorithms, data driven technics also have proven satisfactory results. The neural network (NN) facilitates the rapid inspection applied by many researchers [14]–[17]. In the next, we summarize some important research in this field.

Several researchers have developed an approach: digital damage fingerprints (DDF) to efficiently identify and digitalize characteristics in signals captured from active sensor by online assessment of through-hole and delamination damage in composite structures [18], [19]. Zahoor *et al.* [20] proposed a technic based on automatic of damage using optical time-domain reflectometer and Lamb waves. Rai and Mitra [21] presented a hybrid physics-aided multi-layer feed forward neural network (MLFFNN) model to damage detection using Lamb wave responses. The data collection is based on finite element method (FEM). Su and Ye [8] proposed a technique of damage detection based on Lamb wave scheme and an online SHM with an integrated piezoelectric actuator–sensor network. The proposed method is applied to detect and quantify the through-hole-type defect in the carbon fiber-epoxy (CF–EP) quasi-isotropic laminate. Rizzo *et al.* [17] proposed a method of inspection of pipe by ultrasonic guided waves and automatic classification framework. The extraction of features from raw signals is carried out by discrete wavelet decomposition, Hilbert and fourier transform while ANN allows to classify the size and location of the notch. Lu *et al.* [22] investigates an inverse analysis based on the artificial neural network (ANN) technique to identify crack damage in aluminum plates. Kudva *et al.* [23] presented an approach based on ANN to estimate the damage size and the location by measuring strain values at discrete locations. Agarwal and Mitra [24] studied the matching pursuit (MP) with ML algorithms such as ANNs and support vector machines (SVMs) to automatically detect the damage in aluminum plate. Zhang *et al.* [25] proposed a ML approach to predict damage by Lamb waves. Diverse types and sizes were considered to train the model. A ML method, SVM, was adopted to feed the model. A grid searching (GS) technique was applied to optimize the parameters of the SVM model. Melville *et al.* [16] applied a deep learning by ultrasonic guided waves to automatically detect the damage. The authors have revealed the importance of signal processing to improve data driven models like de-convolution and MP. These technics allow the enhancement and the improvement of defect detection as reported in [24], [26]–[30].

In this paper, we study the damage detection based on ultrasonic Lamb waves. The detection is automated by ML algorithm; ANN model is developed by MATLAB algorithm. The amount of data needed to train the model is reduced by considering only two successive peaks. These features are extracted by CWT technic with Morlet as mother wavelet type. As Lamb waves are complicated to study, only one propagating mode is considered. Pulse echo configuration is adopted in this work with the excitation of S_0 mode alone. The interactions of the excited mode with the defect are recorded for 300 simulations. Each case considers a specific scenario in terms of Lamb waves frequency and damage position.

The present paper is organized as follows. After the introduction of the subject, simulation parameters of Lamb waves in the plate model are reported. In the next section, signal processing by CWT technic is described. The third part shows the ANN schema and the data organization. The performance of the proposed ANN, results and the validation are presented in the last section. The conclusion summarizes the results and proposes future work.

2. METHOD

The method as illustrated in Figure 1, is divide into three main steps, namely the numerical modeling, the data-set preparation, and the evaluation of ANN model. The first step is the numerical modeling of Lamb waves and the extraction of S_0 mode interactions with different cases of defect position and for 6 different frequencies. The data-set preparation is made by signal processing of 300 signals corresponding to 300 cases by CWT. The last step is the evaluation of the proposed ANN model, the hidden layer number is chosen based on the lowest MSE value. The two last steps are repeated until getting the best performance of ANN model.

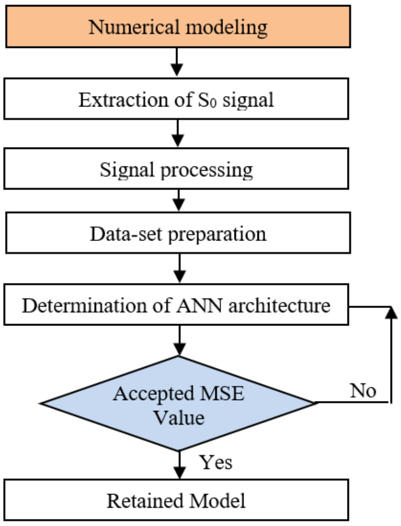


Figure 1. Methodology of the proposed technic

3. SIMULATION OF LAMB WAVES

The numerical simulations help in collecting the data of the considered model. We constitute the dataset of the ANN model by finite element simulations carried out in Abaqus-explicit software. The 300 signals were recorded as a response of the aluminum plate under a specific excitation.

3.1. Damaged plate

We consider in this study a thin aluminum plate of 1 m length and 1.2 mm thickness. The plate contains a rectangular notch of 2×0.8 mm as illustrated in the Figure 2. The characteristics of the isotropic plate are mentioned in the Table 1. The proprieties of the material are Table 1.

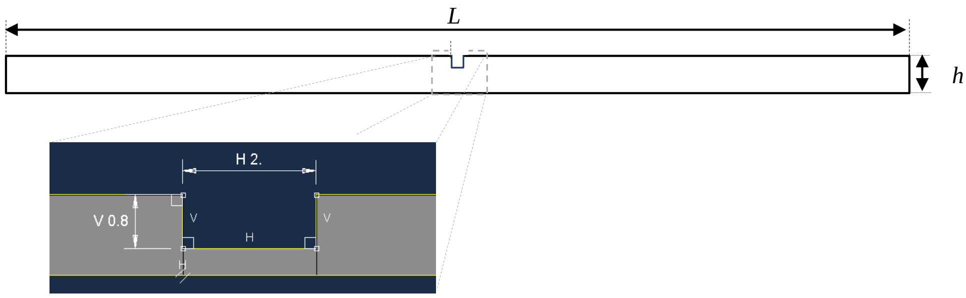


Figure 2. 2D view of damaged plate

Table 1. Proprieties of aluminum plate

Density (kg/m3)	Poisson ratio	Young's modulus (GPa)
2712	0.3	70

3.2. Damaged plate

The simulation of Lamb waves is carried out by ABAQUS explicit. We assume the plane strain approximation. The plate is meshed by CPS4R: a 4-node bilinear plane stress quadrilateral, reduced integration. To ensure the convergence of numerical solution, the time step and element size are calculated in (1) and (2):

$$Element\ size \leq \frac{\lambda_{min}}{20} \tag{1}$$

$$Time\ step \leq \frac{1}{20\ f_{max}} \tag{2}$$

The excitation is sinusoidal with 3 cycles of frequencies ranging from 100 kHz to 225 kHz with step of 25 kHz. The Figure 3 shows the pulse echo configuration considered in this study. The distance d and frequency of the excitation Figure 4 will be changed to constitute the data set of ANN model.

3.3. Verification of S_0 mode propagation

Lamb waves are multi-modal, that makes it challenging task when it comes to study their interactions with the defect. Based on semi analytical FEM [31], the Figure 5 showed the variation of group velocity versus the frequency. The arrival time for the case of 100 kHz is 2.36 E-5 s. Given the distance between the actuator and the sensor is 125 mm. The group velocity is then V_g=5296 m/s. In comparison with the analytical value 5340 m/s, this corresponds to the fundamental symmetrical S_0 mode with a relative error of 0.82%.

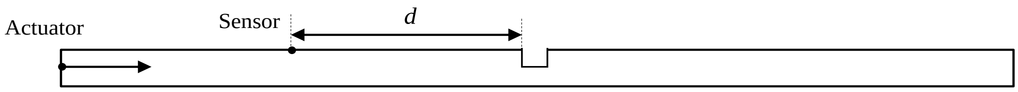


Figure 3. Pulse echo configuration and excitation of S_0 mode

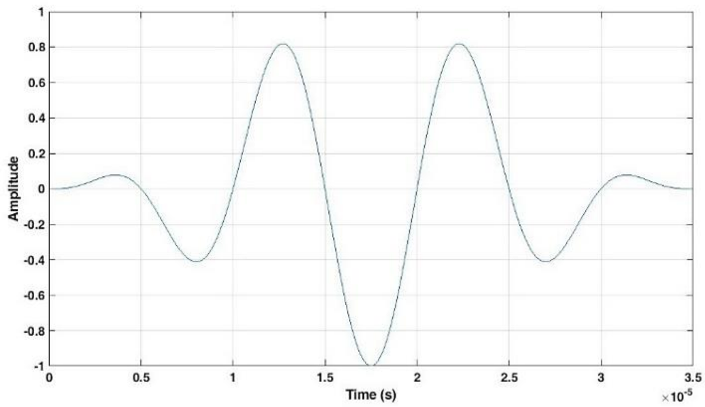


Figure 4. Tone burst excitation signal at 100 kHz

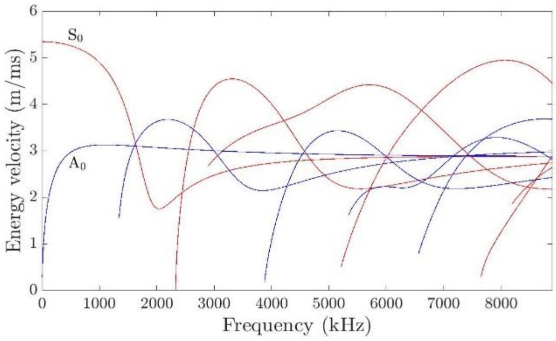


Figure 5. Group velocity dispersion curves of Aluminum plate (thickness of 1.2 mm)

3.4. Extraction of S_0 mode interactions for various damage cases

In this part, we consider different scenarios of defect positions. As mentioned before, by variating the distance *d* between the artificial defect and the position of sensor we get different features. Lamb waves are highly sensitive to defect, but more the defect is small, more we require the input frequency to be high. For that reason, we recorded the signal of S_0 mode for six different frequencies. In fact, the S_0 mode reflected back from the discontinuity contains damage information's. It corresponds to 19 cases (different *d* positions) and for different frequencies as shown in Figure 6.

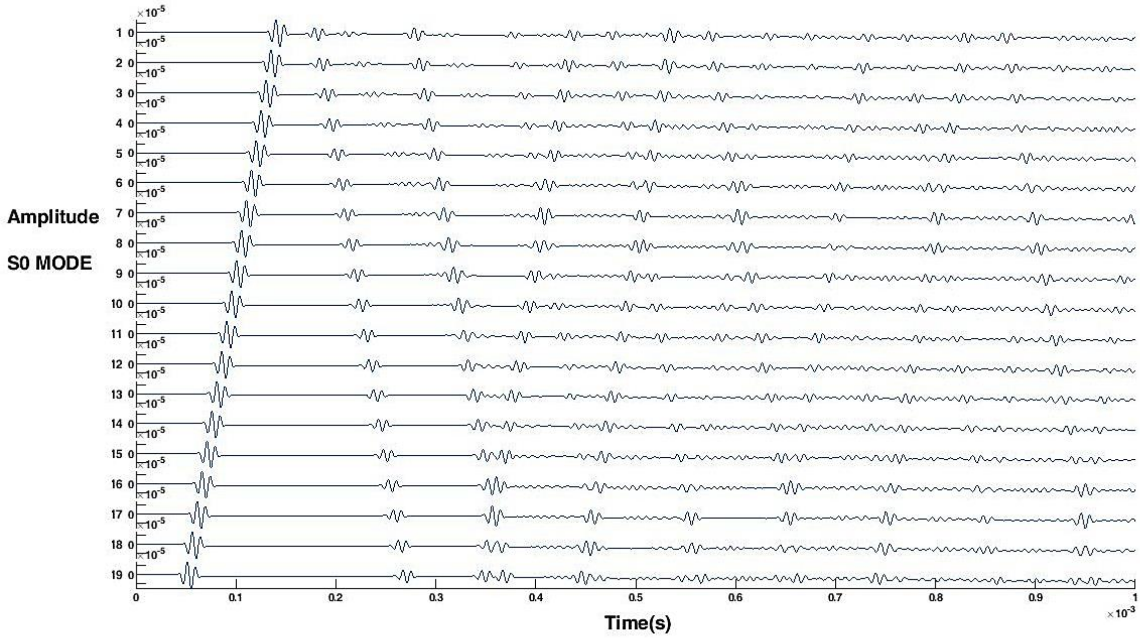


Figure 6. Extracted responses at 100 kHz of S_0 Lamb mode for 19 damage cases

4. CONTINUOUS WAVELET TRANSFORM OF S_0 MODE SIGNALS

Building the data set of ANN model require choosing the key features of recorded signals. The optimal features are up to now unanswered. We aim to detect automatically the position of the defect, so we assume that the main feature is the arrival time. As we have opted for the pulse echo configuration, the position of the defect relatively to the sensor can be calculated by knowing the two successive peaks. So, CWT is a best tool to know the time of maximus amplitude in the recorded signal. This method is a time-frequency analysis technic that dealing with several types of signals. The wavelet transform is applied to identify the defect in many mechanical structures [32], [33].

In this paper, we employ the CWT to locate the time arrival of the two first peaks. The wavelet coefficients are calculated in (3) [34]:

$$W_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \tag{3}$$

where $x(t)$ is the signal and $\psi(t)$ is the continuous mother wavelet that is scaled by a factor of a and translated by a factor of b. The superscript * symbol denotes the complex conjugate.

One of the widely used and most well-known is the Morlet wavelet, that is defined as a sine wave multiplied by a Gaussian envelope.

$$\psi(t) = e^{i\omega_0 t} e^{-t^2/(2\delta^2)} \tag{4}$$

Wiht δ and ω_0 are constants; ω_0 represents the wavelet center frequency. In the frequency domain, the dilated version of Morlet wavelet is given by:

$$\Psi(\omega) = \delta\sqrt{2\pi}\, e^{-(a\omega-\omega_0)^2\delta^2/2} \tag{5}$$

Figure 7 shows the two peaks calculated by CWT applied to the signal at the frequency of 125 kHz.

5. ARTIFICIAL NEURAL NETWORK MODEL

In this paper, ANN network is implemented by MATLAB toolbox, with two-layer feed forward with sigmoid hidden and output neurons. The ANN model is trained with scaled conjugate gradient back propagation. Seven neurons in the hidden layer have been used as presented in Figure 8.

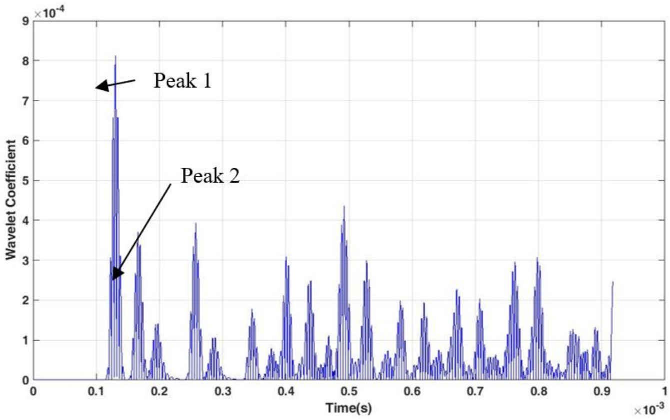


Figure 7. CWT applied to the signal of 125 kHz

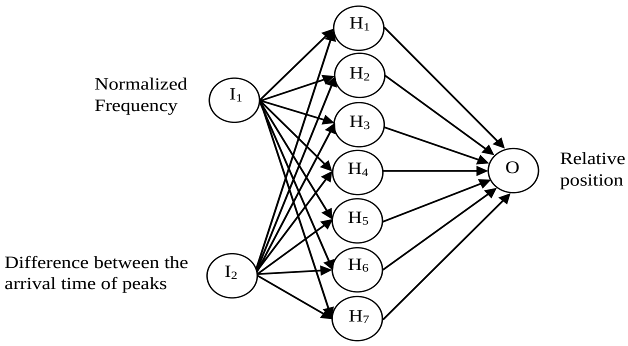


Figure 8. Architecture of ANN implemented model

5.1. Preparing data

In this study, 300 cases were selected as input data. To optimize the data analysis, we use CWT in order to pick up only the time of flight and important features from raw data. The first input data consist of two columns. In the first column, the time and in the second the displacement extracted from various damage cases. The second data is the frequency of the excitation. The input data are normalized by their maxima.

5.2. Performance of the artificial neural network

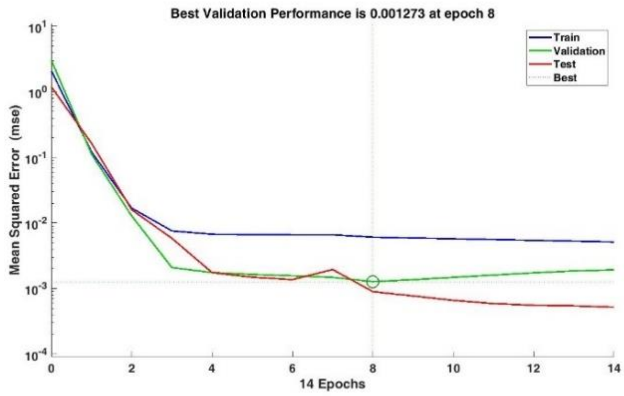
The performance of ANN model depends on the appropriate selection of neuron numbers. Based on previous works and experiences, the number of neurons can be determined by the relation in (6) [35]:

$$i = \sqrt{p + q} + B \tag{6}$$

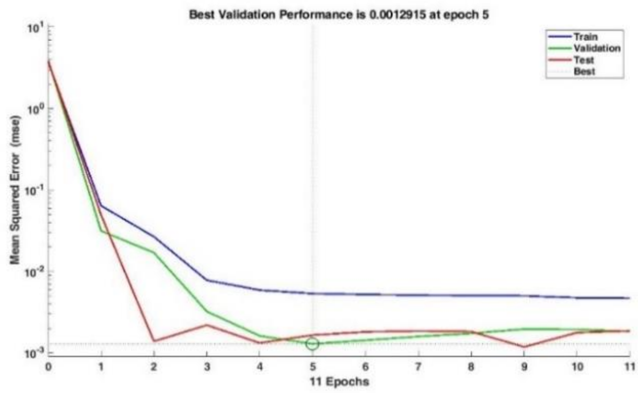
with i, p, and q are the number of neurons, input elements and output elements for each hidden layer, respectively. B is an empirical constant ranging from 4 to 8, depending on different applications. To evaluate the performance of the proposed model, a series of different schemas by varying the number of neurons in hidden layer are tested. By applying in (6), four neurons number in the hidden layer are tested. The generalization of the model is evaluated by varying the number of neurons as presented in the Figures 9(a) to 9(d). The learning curve showing the variation of mean square error (MSE) versus epochs plot. Here the learning of four models with different number of neurons in the hidden layer.
The value of the mean of squared error is calculate in (7):

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{7}$$

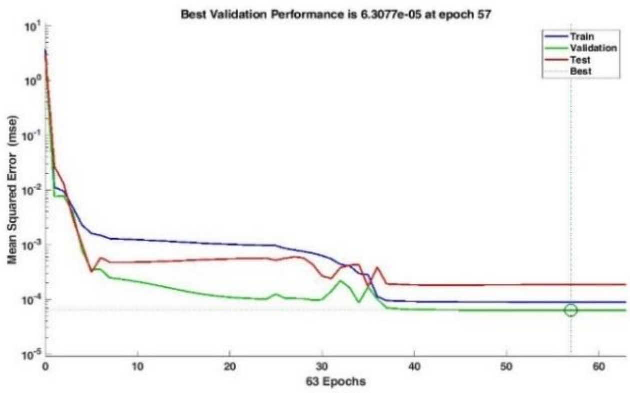
with N is the number of data, $\hat{y}_i$: the prediction value and y_i is the target value.



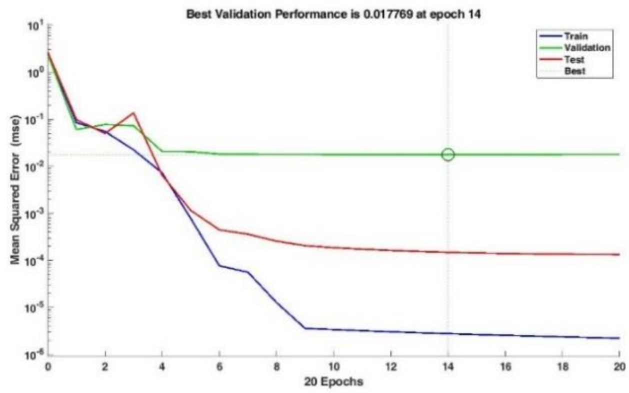
(a)



(b)



(c)



(d)

Figure 9. Performance plot for different ANN schema: (a) 5 neurons, (b) 6 neurons, (c) 7 neurons, and (d) 8 neurons

The best configuration, where the difference of validation error and training error is very small, is showed in Figure 9(c) which demonstrates a stable learning performance. In this configuration, the ANN model predicts the position with a MSE of 6.3077E-5 at epoch 57 as illustrated in the Table 2.

Table 2. Comparison of the ANN performance for different neurons number

Number of neurons	MSE	Epoch
5	1.273 E-3	8
6	1.2915 E-3	5
7	6.3077 E-5	57
8	1.7769 E-2	14

6. RESULTS AND DISCUSSION

In the previous section of our paper, we have shown that the performance of the proposed model depends on the number of neurons. The best case is when the number equals seven. The Figure 10 shows the regression plot with an average linear regression value of 0.9998. The proposed model can predict the damage location with an accuracy of 99.98%.

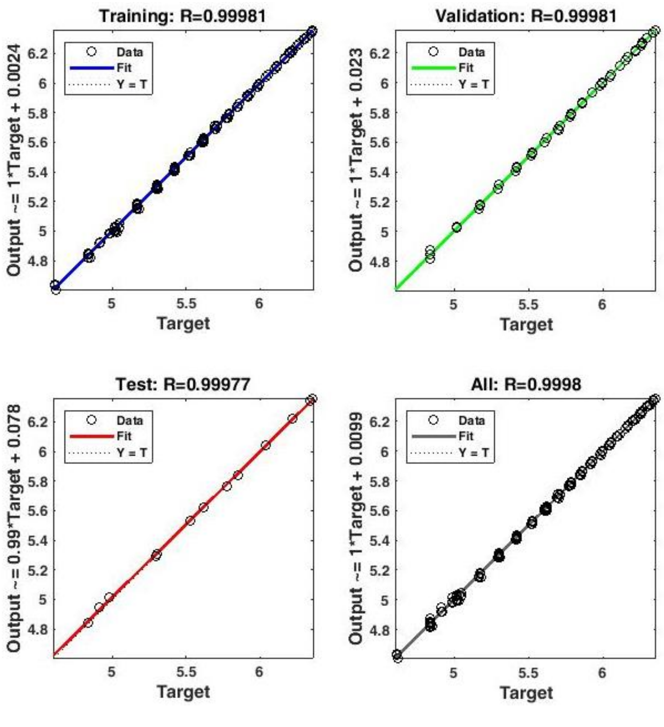


Figure 10. Linear regression of proposed model

7. CONCLUSION

In this paper, an ANN model has been proposed as an automatic damage detection technic. The suggested model is verified and found to be suitable and excellent for SHM. The study attempts to automate the prediction of the defect position by optimization the input data. Firstly, by considering monomodal propagating Lamb mode which is symmetrical S_0. Secondly, by taking into consideration different frequencies from 100 kHz up to 225 kHz and thirdly by applying the CWT to pick up the key features driving the valuable information of the considered defect. The algorithm reaches an excellent level of generalization and predict the defect position with an accuracy of 99.98 %. Lamb waves modes demonstrates to be a good technic and proves a high sensitivity towards defect type notches, specially S_0 mode. To achieve more accuracy and to train our model, experimental data set will be considered in our future work. Also, more frequencies will be considered to extend our model and to predict the smallest defect. In this work, only position was predicted, we will develop our model to also estimate the size of the defect.

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