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Application of artificial neural networks for damage indices classification with the use of Lamb waves for the aerospace structures.

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Abstract. Lamb waves (LW) are used for damage detection and health monitoring due to the long range propagation ability and sensitivity to structural integrity changes as well as their robustness in different applications. However, due to the dispersive character and multimode nature of LWs, analysis of the acquired ultrasonic signals is very complex. It becomes even more difficult when applied to a complex structure, for instance, an aircraft component with riveted joints and stringers characterized by difficult geometries. Therefore, numerous approaches to the evaluation of damage indices have been proposed in the literature. In this paper, comparison a number of damage indices applied to LWs testing in aircraft aluminum panels. The damage indices, known from the literature have been selected from the application point of view. Artificial neural network has been used for the classification of fatigue cracks and artificial damages induced in the specimens taken from a real aircraft structure. Article presents results of simulation, data analysis and data classification obtained using selected and dedicated neural network. The main aim of the presented research was to develop signal processing and signal classification methods for an aircraft health monitoring system. The article presents a part of the research carried out in the project named SYMOST.

Introduction

SYMOST Project. The problems of health monitoring of aircraft structures throughout the operational phase (operation and maintenance) are very complex and complicated. The loads spectrum that affects the structure depends first and foremost on the way the aircraft is operated, hence, there is no chance to precisely design the aircraft life before it enters the operational use. The idea of the project is to produce a system for health monitoring of the load-carrying structure of the PZL-130 TC II „Orlik" aircraft. The PZL-130 Orlik is a light, single engine trainer to provide training in the flying skills. The aircraft was designed in the 1980s in Poland. The project is aimed at developing a technology demonstrator in the form of a system to monitor aircraft structure that enables the diagnosing and early warning against a catastrophic failure. The system will be based on piezoelectric sensors which being coupled with the object under examination, will enable generation of measuring signals (elastic waves) in the component exposed to the test. System will be validated during the full scale test of the aircraft and the results will be correlated with the Non Destructive Inspection NDI techniques used for this aircraft. Moreover the results of the final teardown of the aircraft structure will prove the efficiency of the used techniques. The expected result of the project is to develop the system which will be capable to detect, classify and locate the damage presence and its size. One of the part of the project is the elaboration of the techniques for signal modeling, processing as well as damage classification. The approach presented in the article is based on the Neural Network for damage classification.

Structure monitoring with the use of guided waves. Aircraft structural elements have to stand high safety standards, therefore an increasing awareness of the importance of damage prognosis systems can be observed in the recent years. These systems can bring potentially enormous benefits, since the schedule-driven maintenance procedures can be replaced with the condition-based ones, which allows to shorten the period in which the aircraft is offline due to inspection and results in cost savings and most of all safety increase [1].

Many aircrafts' components, for instance skin panels, stringers, are thin-wall elements, thus can be monitored using Lamb waves (LW) due to the long range propagation possibility and sensitivity to structural integrity changes. However, due to dispersive character and multimode nature of the waves, the acquired signals are very complex. They become even more difficult to analyze in complex structures, for instance aircraft components with riveted joints, stringers and difficult geometries.

A well-known approach is application of sparsely populated networks of transducers spread over the investigated structure [2]. If the structure is complex it is difficult to distinguish damage-reflected signals from the boundaries reflections, therefore the monitoring normally involves a set of baseline signals captured from a healthy structure. Next, the snapshots acquired during operation are compared with the baselines, which are calculated as damage indices (DI) describing the condition of the monitored element. Numerous approaches, involving various signals' features extraction, for DI evaluation were proposed in the literature [3]. A closer look to the selected methods and DI will be given in the further part of this paper.

Numerous DI can be calculated for a given condition of a structure. Various DI present different sensitivity not only to structural integrity changes, but also to noise and environmental conditions [4]. In a case in which numerous DI are used simultaneously, multi-dimensional parameter space cannot easily be divided by arbitrary chosen classification threshold levels. In order to perform classification of regions in parameter space, which refer to the specific state of structure, artificial neural networks (ANN) can be used.

Artificial Neural Networks in SHM. Artificial Neural Networks (ANN), due to their "intelligence" – which is the ability to generalize on incomplete data, are used with great success in SHM and NDT. Usually the learning process, (which is supervised learning), is performed on laboratory or simulated data, which, as a result, leads to successful classification of actual damage data.

Neural networks for damage classification in general are based on pre-processing data which would lead to delivery of damage indices vector. Given vector is then used by the network to perform classification. If such method is utilized, the network structure remains independent of the type of data classified and can be used in all fields of NDI: Vision based measurement [7,8,9], radiography, [10,11,12], thermography ([13,14]) or ultrasonic testing [15,16,17,18,19].
The most commonly used architecture of ANN is the least difficult to implement and teach - Multi Layer Perceptron network, which divides an n-dimensional parameter space into k classes, where n is the number of input neurons (parameters) and k – the number of output neurons. Despite its simple structure, the network performance is comparative to other more sophisticated networks. [16]

To solve the problem of damage identification based on a damage indices vector other structures are also used (e.g. LVQ (Learning Vector Quantization), RBF (Radial – Basis Function networks), SVM(Support Vector Machines)) [16].

Numerous examples of neural network classifiers for damage detection in ultrasonic testing have been proposed in literature. However, specimens used there are usually simple [13] and damages induced (usually in the form of radial holes or notches) are large in comparison to specimen's dimensions.

Taking into consideration the information listed above, especially the little difference in efficiency of MLP and alternatives, the authors decided to utilize MLP network with two hidden layers as a classifier tool for Lamb-wave measurement results. Due to the fact, that five damage indices were to be used simultaneously, five-dimensional parameter space cannot easily be divided by arbitrary chosen threshold levels. Moreover, usage of ANN will allow further modifications of the DIs, especially utilization of large number of DIs in the future. ANN is used in this instance to perform successful classification of regions in parameter space, which refers to the specific state of structure (lack of damage or specific level of damage). This paper is organized as follows: a brief theoretical background to DI evaluation and their ANN classification, next the proposed classification technique is demonstrated based on simulations and experiments in which damage was introduced as a mechanically made notches. Finally the classification was generalized for experimental data collected during fatigue tests. A discussion and conclusions are given in the final part of the paper.

Theoretical background

In order to place the presented approach into context an evaluation of selected DIs will be given below. Next a brief theoretical background of DIs classification using ANN will be described.

Damage indices. Damages occurrence in a structure affect propagation of LWs which influence the acquired signals. The aim of DIs evaluation is to extract and quantify damage-related features. In this section five indices used to quantify difference between a signal *y(t)* and a baseline *x(t)* will be presented. Note that although the DIs are calculated in a discreet time, continues time is used here for clarity of demonstration.

The first differential feature, presented here, is normalized squared error between the signal and baseline calculated in time-domain according to the expression:

$$DI_{TDRMS} = 1 - \frac{\int_{t1}^{t2} \left[y(t) - x(t)\right]^2}{\int_{t1}^{t2} x(t)^2\, dt}, \tag{1}$$

where t_1 and t_2 denote time intervals in which the integration is performed [3].

The next two DIs were based on cross correlation of the signal and the baseline. In the first approach the DI was calculated using the following expression:

$$DI_{XCOR} = 1 - xy(\tau = 0), \tag{2}$$

where $xy(\tau)$ is cross correlation coefficient of the baseline and the response obtained for lag of 0. The principle for this DI is that if the baseline and response are identical the cross correlation becomes autocorrelation with peak at the level of 1 at $\tau=0$. The main advantage of this DI is that it is sensitive only to changes in the shapes of the signals, and not to their amplitudes [6].

In the second approach the DI is evaluated similarly to the previous one, however in this case the maximal value of the cross correlation is used, regardless of τ at which it occurs. Therefore the formula becomes:

$$DI_{\max XCOR} = 1 - \max(xy(\tau)). \tag{3}$$

The DI is insensitive to time-shifts between the baseline and the response.

Two last DIs were evaluated as a difference between envelope of the signal and baseline. It can be calculated using the following expression:

$$DI_{env} = \frac{\int_{t1}^{t2} \left[Y(t) - X(t)\right]^2 dt}{\int_{t1}^{t2} X(t)^2 dt}, \tag{4}$$

where *X(t)* and *Y(t)* denote envelopes of the baseline and the signal respectively. Two methods for envelope evaluation were used: Hilbert transform and continuous wavelet transform (CWT). In the implementation based on CWT complex Morlet wavelet was used as a mother wavelet.

Aim of experiment and the methods selection

The aim of the experiment was to develop classification method for the measurement data obtained from the Lamb wave measurements. The classifier should be trained on laboratory data from artificial damage introduced to specimen taken from an aircraft structure, and be able to perform successful classification of real-life data from fatigue test leading to emergence and development of the fatigue cracks in a part of an aircraft structure.

Experimental setup and damage indices extraction

Artificially induced damage. In order to evaluate damage indices value and to perform learning process of ANN, a series of tests on fragment of aircraft's structure were executed. The experiments were conducted on an aircraft panel illustrated in Fig. 1. The panel was instrumented with eight PZT transducers SMD07 provided by Steminc, USA. As a signal generator and data acquisition unit PAQ 16000D from EC Electronics, Poland was used. The excitation signal consisted of 8 cycles of sine modulated with Hanning window. Two excitation frequencies were used: 100 and 200 kHz.

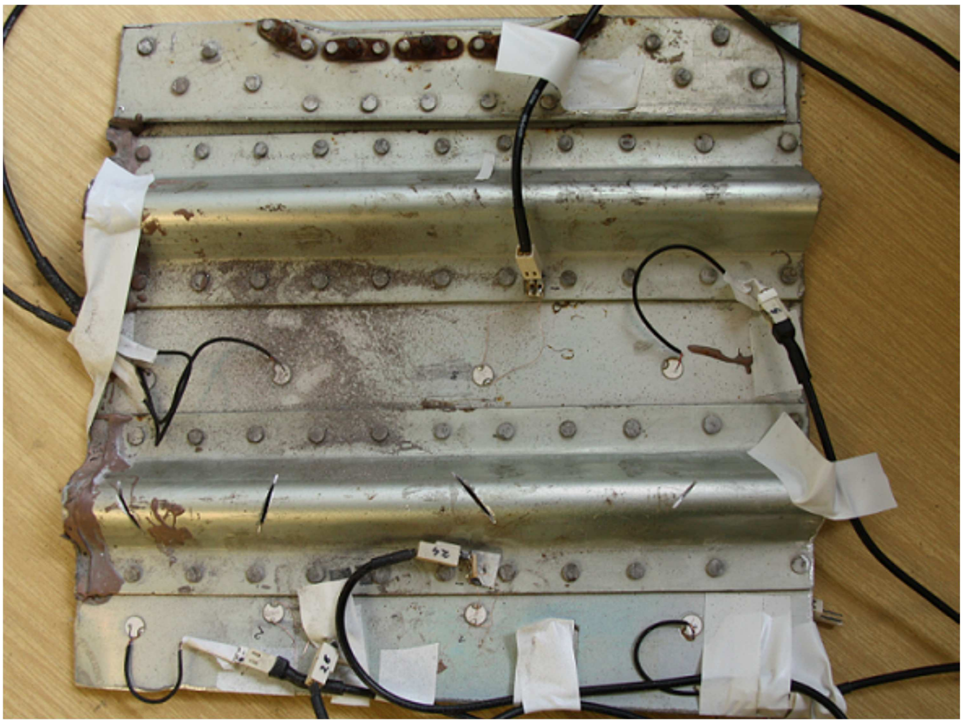

Fig. 1. The specimen used for tests

Fig. 2. First stage of damage induced

Fig. 3. Last stage of damage induced

In the first part of the experiment, a series of reference measurements were performed in conditions of small temperature changes during the day. The tests were taken every 1 hour during 48 hours. The main point of that task was to define the spectrum of damage indices changes when there is lack of damage. In the next part of experiment, the specimen was damaged through cutting. Each of the four cuts were increased eight times, from the state of scratch of surface (Fig. 2) to the large notch around 20 mm long. (Fig. 3). Before each stage of increasing the notch, measurement was performed, except for the beginning of cutting where two measurements were executed for the reference.

The collected time series were used to compute damage indices in accordance to algorithms presented in theoretical background. As each of the transducers were used respectively as an transmitter and the frequency of generated wave was 100 kHz and 200 kHz, one measurement consisted of 128 time series. Thus from one measurement 128 five-element vector was obtained, which stored calculated damage indices values.

In the Fig. 4 damage indices values alternations for 48-hours reference test are shown. In the fig. 5 alternations of the same damage indices values on the same measurement line for 9 stages of damage growth are presented. Start from measurement no 5 (corresponding to notch length of approximately 10 mm) value of damage index exceeds those obtained during reference measurements.

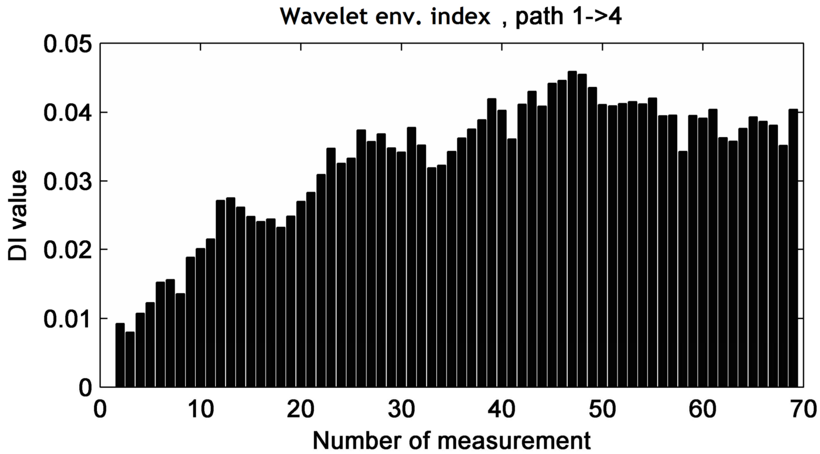

Fig. 4. Changes in damage index values during 48-hours reference test on one exemplary measurement line

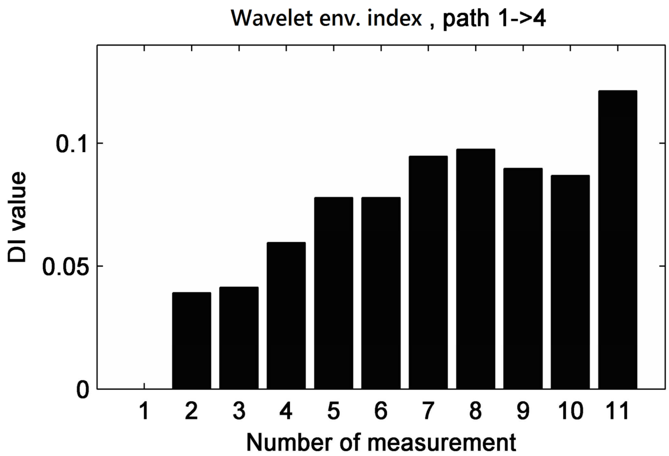

Fig. 5. Changes in damage indices values during experiment

Fatigue crack growth detection. For the purpose of the accelerated trials of the SHM system for the damage growth description, series of fatigue tests on the subcomponent scale were delivered and are going to be continued. Fatigue tests were performed on the MTS 810.23 fatigue machine. The specimens selected for the tests include diversity of selected 'hot spot' locations in the aircraft structure.

That takes into the consideration fatigue cracks development in the: aircraft skin, fasteners row, subcomponents (stringers and ribs), holes and geometry changes, jackets and attachments. Such approach for the experiment gives the possibility of the different damages scenario simulation. During the tests the fatigue crack growth was observed and additionally the damage size was registered with the use of NDI. Finally, at the end of the test the correlation between the NDI and the SHM system is delivered.

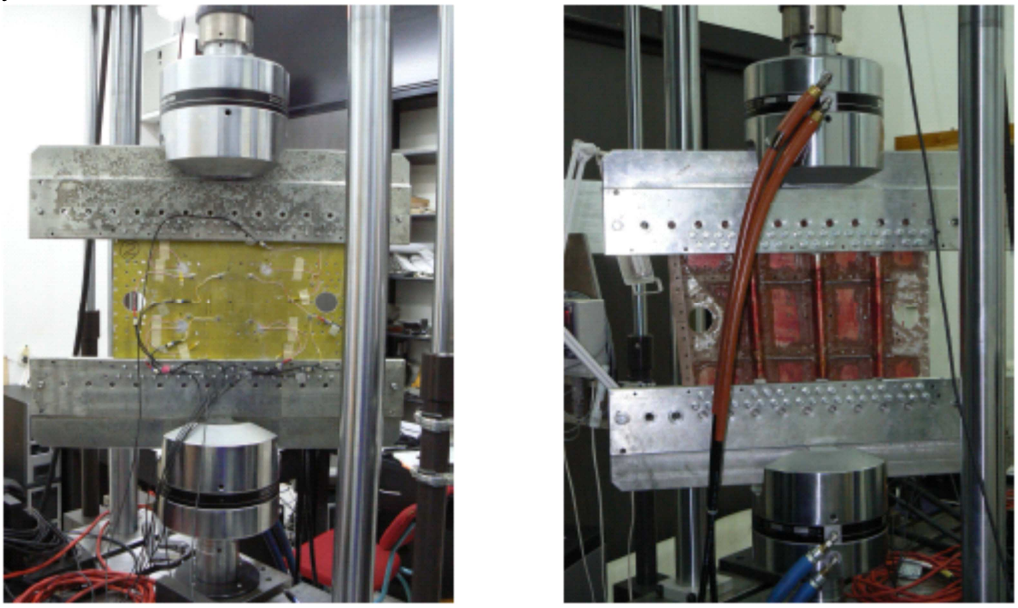

Fig. 6 – Test bed visualization (fatigue test on stringers)

In the Fig. 6 the test bed visualization is presented. The picture presents test for the development of the fatigue crack in reinforced panel (crack in stringer). The force value for test run for the riveted panel was equal to 35 kN and the cycle number was equal to 1000 cycles. During the test the consecutive 1000 cycles series were increased from the 5 kN up to 75 kN. The total fatigue cycles number was equal to 14 000.

Data processing

In order to perform learning process of the ANN, two matrixes were prepared based on the measurements described above: "Input" matrix with damage indices values for all measurements and "Target" matrix with the stage of damage. Evaluation of the real stage of damage that should be assigned to given damage indices vector is complicated task due to the fact that distance between the damage and sensing path has great influence on the indices. The number of measurements was large, therefore, the authors decided to generalize and assign the same damage growth pattern to each measurement line. It was stated, that to the first two reference measurements "0" value of damage should be assigned. To the last four measurements value "1" (maximal damage) should be assigned and to the measurements from 3 to 7 linear growth of damage (values from 0 to 1 are assigned). An example of damage index's values and target damage values for one sensing path is shown in the Fig. 7.

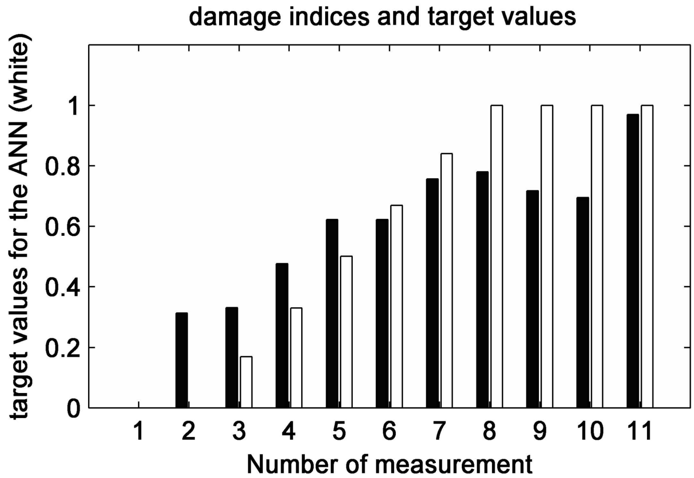

Fig. 7. An example of damage indice value changes (black) and target damage values transferred to the network (white)

Learning process on given data was performed with back-propagation method, with use of *Levenberg-Marquardt* algorithm.

Testing set was prepared in similar manner: Measurements for all data lines were treated collectively. The value "0" of damage was assigned to first two measurements on each measurement line whereas "1" as value of damage was assigned to last four. Remaining measurements were expected to have linear growth of damage. Vectors, computed for each measurement line damage indices, were presented to the network, the network response was compared to the expected value of damage.

Results

In order to get more general knowledge of network's performance, learning and testing processes were performed 100 times. An example of neural network classifications for two measurement lines during all performed tests is presented in Fig. 8. The crosses represent correct value of damage for given measurement. (Note: this value is determined arbitrarily and may not refer to actual damage state as the real state of damage is difficult to determine). The dots represent neural network responses in 100 tests, the circles represent errors (Difference between expected correct value of damage and network's response) .

Overall classification error achieved in the experiment (which is an average of all tests performed and all classifications during one test) was 0.086.

It was decided, that the set arbitrarily correct value of damage over 0.6 is treated as a significant and should be detected, while the correct value of damage below 0.2 is treated as a non-damaged state.

Classification result returned by the network is used to determine whether the specimen is damaged or not. The level of the network's response at which the damage is thought to be present is set on the basis of the chart presented in Fig. 9. The curves represent the amount of false indications (of the damaged and non-damaged states) as a function of threshold value. The level of threshold was set to level 0.5 due to the fact, that in aircraft SHM there is necessity to maximize probability of damage detection as a function of possible false alarms (lack of damage treated as damage).

The averaged results of all performed tests for the threshold value set at 0.5 are listed in tab. 1. Network noticeably better infer on set of damaged data, which is caused by safe choice of threshold level.

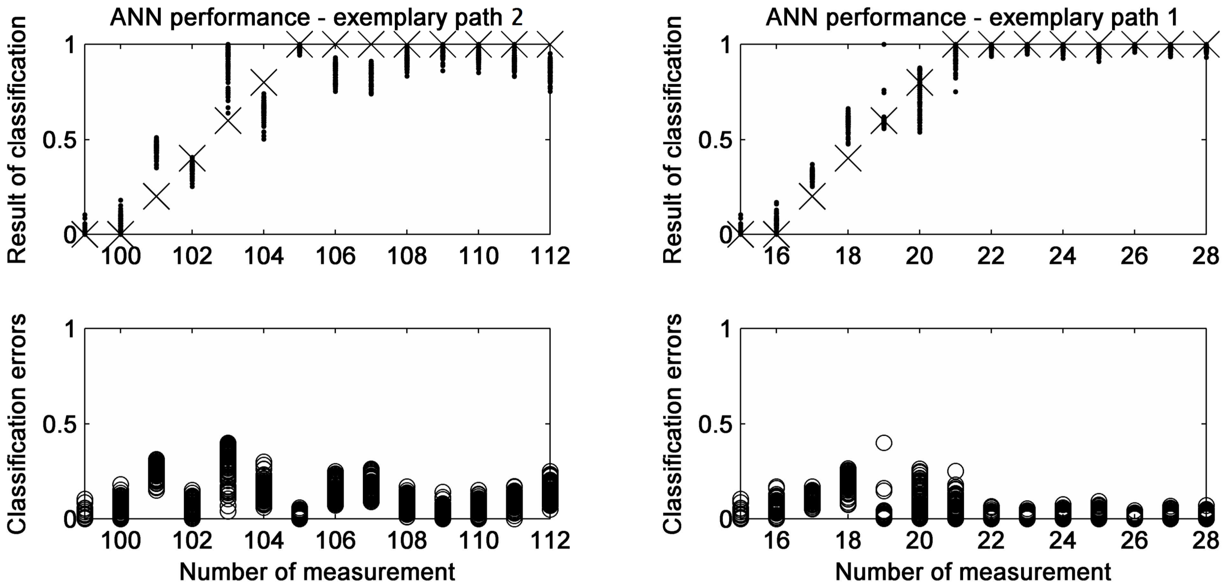

Fig 8. ANN response (dots), Expected values of damage (crosses) and classification errors (circles) for the two examples of measurement paths

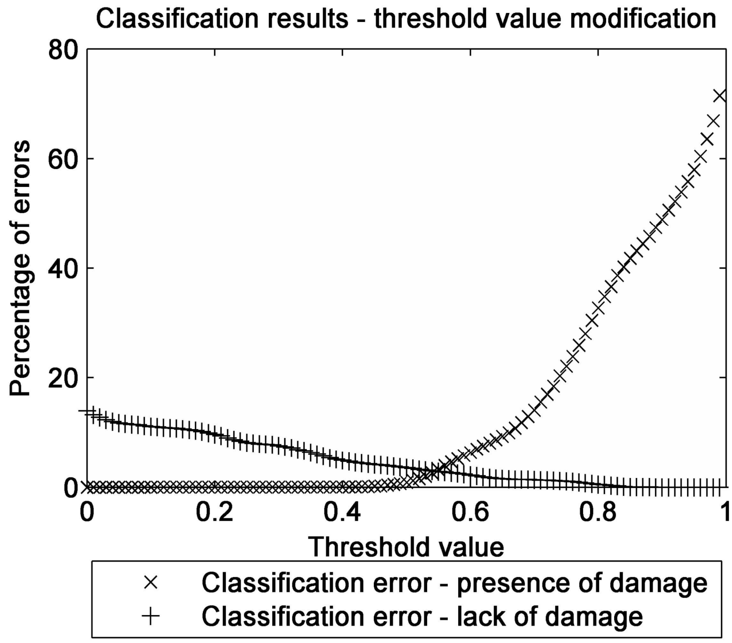

Fig. 9. Influence of threshold value on result of classification

Tab. 1 Results of testing on the data set obtained from fatigue test

	Reference	Damage
Number of measurements	144	432
Number of correct matches	122.82	422.87
Number of errors	21.16	9.11
Percentage of correct matches [%]	85.29	99.55
Percentage of errors [%]	14.70	2.11
Overall classification error	0.086	

Conclusions

The Artificial Neural Network performs well as a tool for damage indices-based classification of experimental data obtained from Lamb-wave testing of real-life specimens with fatigue cracks. Damage indices used by the authors have sufficient sensitivity to distinguish damaged and undamaged state of the specimen. The learning process of an ANN performed on specimens with artificially induced damage allows the network to accomplish successful classification of the real-life specimens with different structure, different sensor placement and different damage (fatigue cracks in contrast to artificial notches).Therefore, the MLP network that operates on proposed DIs can be a part of an autonomous diagnostic system for monitoring the state of an aircraft during its operation.

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