ANFIS-Wavelet Packet Transform Approach to Structural Health Monitoring

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***Abstract*— In this paper, a structural damage identification approach is proposed which combines adaptive network-based fuzzy inference system (ANFIS) and wavelet packet transform (WPT) technologies. The approach is referred to as ANFIS-WPT. For each measured structure vibration response signal, WPT is first applied to extract a feature vector representing its energy distribution in different frequency bands. Based on its energy percentage contribution, selected elements of the obtained feature vector are taken as inputs for the ANFIS. The output of the ANFIS is a condition index, which can be a Boolean value (0 or 1) for level 1 damage assessment use (damage detection), or a number of values for level 2 damage assessment use (damage localisation). Provided an ANFIS model is well trained by the available data, it can be used for health monitoring and damage localisation. The proposed approach was applied to the data obtained from an experiment involving a cantilever beam for damage detection and localisation. The testing results show that the method is successful in detecting and classifying structural damage.**

***Index Terms*—ANFIS, Wavelet transform, Structural damage detection.**

I. Introduction

Damage in structural and mechanical systems is defined as *"changes to the material and/or geometric properties of these systems, including changes to the boundary conditions and system connectivity, which adversely affect the current or future performance of these systems."* [1]. For safety reasons and because of the economic benefits that can result, the interest in the ability to detect and locate structural damage at the earliest possible stage is pervasive throughout the civil and aerospace engineering communities.

Damage identification methods can be classified into four levels of damage assessment [2]: level 1 (detection): determination that damage is present in the structure; level 2 (localisation): level 1 plus determination of the geometric location of the damage; level 3 (quantification): level 2 plus quantification of the severity of the damage; level 4 (prediction): level 3 plus prediction of the remaining service life of the structure.

The objective of this study is to develop methods for structural damage detection and localisation (i.e. level 1 and level 2 damage assessments) based on the WPT and ANFIS technologies. The work of this paper is organised as follows. In section II a short background to WPT and ANFIS are given. Section III discusses the utilisation of WPT as feature extractor for structural damage identification. Then, in section IV, the ANFIS-WPT approach to structural damage identification is presented. The effectiveness of the proposed method is demonstrated in section V by analysing the vibration response data from a cantilever beam. Concluding remarks are given in section VI.

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II. Background

A. Wavelet Transform

In the wavelet transform (WT), a signal $f(t)$ is written as a series expansion in terms of wavelet families [3]:

$$f(t) = \sum_{k=-\infty}^{+\infty} < f(t), \quad \varphi(t-k) > \varphi(t-k) + \sum_{j=-\infty}^{-1} \sum_{k=-\infty}^{+\infty} < f(t), \quad \psi_{j,k}(t) > \psi_{j,k}(t) \tag{1}$$

where the father wavelet family { $\varphi(t-k), k \in Z$ } is used to describe the smooth part of $f(t)$, the mother wavelet family { $\psi_{j,k}(t)$, $j \geq 0$ } is used to describe the details of $f(t)$ at different levels. This kind of expansion can expose the information originally hidden in $f(t)$.

An efficient way to implement the WT, and its inverse (IWT), is to use filter banks and down-sampling/up-sampling techniques developed by Mallat [3]. Moreover, the connection of WT with filter banks is a tool to understand the frequency allocation property of WT. For example, Fig. 1(a) shows a 2-level discrete wavelet decomposition and reconstruction which demonstrates the idea of using filter banks to calculate WT and IWT. The original signal $f(t)$ is broken down into three sub-signals: A_2, D_1 and D_2. From $f(t)$ to A_2, D_2, D_1, the whole process could be seen as passing $f(t)$ through three filters (see Fig. 1(b)). Each filter has different frequency characteristics and thus a frequency allocation is achieved via wavelet analysis. For example, the spectrum of the three filters associated with a two-level Haar wavelet analysis is shows in Fig. 1(c). Note that the spectrum is plotted over the range [0, 0.5], where 0.5 corresponds to the Nyquist frequency (half of the sampling frequency). The figure clearly shows that the filter 1 acts as a low pass filter, the filter 2 serves as a band pass filter and the filter 3 can be taken as a high pass filter.

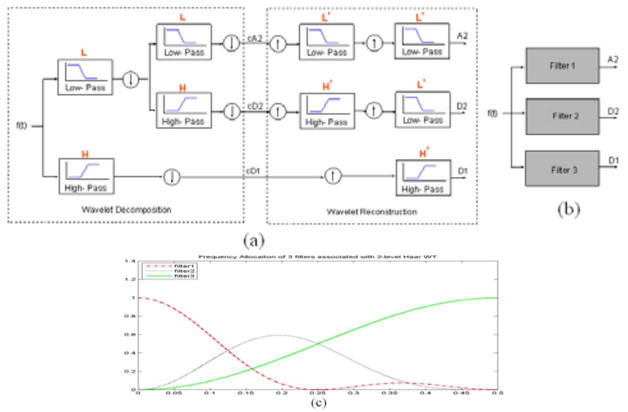

Fig. 1. The filtering process of DWT and IDWT, (a) 2-Level DWT decomposition and IDWT reconstruction using filter banks; (b) the 3 Filters in (a); (c) the frequency spectrum of the three filters associated with a two-level Haar wavelet analysis: -·-·- Filter 1, ···· Filter 2, — Filter 3.

B. *Wavelet Packet Transform*

One possible drawback of the WT decomposition is that produces a logarithmic frequency allocation: the low frequencies have narrow bandwidths and the high frequencies have wide bandwidths. This frequency allocation property is appropriate for some applications but may not be for the current case. In the current study, the WT is used to reflect the energy redistribution in the response signal caused by damage. Since the energy redistributions caused by damage normally take place in the high frequency range, a finer frequency resolution, especially in the high frequency region, may be preferred. This finer distribution is easily accomplished by the wavelet packet transform (WPT). In the WPT, the details as well as the approximations are split. Therefore, the WPT provides a finer and adjustable resolution of frequencies at high frequency regions. For a better comparison, the frequency allocations produced by the full four-level db15 WPT and four-level db15 WT are illustrated in Fig. 2. It is clear that the frequency resolution, especially at a high frequency range, is much finer than that for the WT.

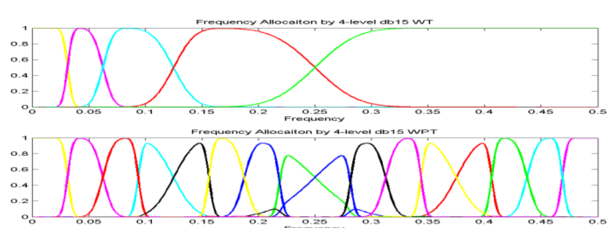

Fig. 2. The frequency allocation by 4-level db15 WT (upper) and WPT (lower).

C. *ANFIS*

There are several approaches to integrate artificial neural networks (ANN) and fuzzy inference systems (FIS), and it can be said that ANFIS is one of the most successful approaches. For a matter of space, the reader interested in a full explanation of ANFIS is referred to [9]. Here it is only said that an ANFIS structure is used for damage classification. The way in which this structure is designed for this task is explained in section IV.

III. Feature Extraction Using WPT

Yen and Lin [4] first adopted the wavelet component energies as the feature vector to detect structural damage. This feature vector is then used by Sun and Chang [5], [6] as an input to neural network models for higher level damage assessment. In the present work, a similar feature vector is used, but differs in that the percentage energy contribution of some selected sub-signals to the original signal is formulated and taken as the feature vector. In addition, instead of using a feedforward ANN for classification, an ANFIS is used. The reason why the percentage energy values are chosen as feature vector lies in the fact that, for a structural response signal, damage in the structure will cause the redistribution of the energy in different frequency bands, which can be easily calculated by WPT.

Here, for convenience, it is assumed that only one accelerometer measuring the structure vibration response is used. For an L- level wavelet transform, the original signal $f(t)$ is decomposed into $L+1$ sub-signals: i.e. A_L, D_L, D_{L-1} … D_1. The energy of a discrete signal $x=[x_1, x_2 ... x_N]^T$ is defined as the sum of its squared modulus:

$$\varepsilon_x \overset{def}{=} \sum_{n=1}^{N} |x_n|^2 \tag{2}$$

The ratio of energy of these $L+1$ sub-signals from $f(t)$ is then defined as:

$$V = \left[\frac{\varepsilon_{A_L}}{\varepsilon_f}, \frac{\varepsilon_{D_L}}{\varepsilon_f} .... \frac{\varepsilon_{D_1}}{\varepsilon_f} \right] \tag{3}$$

where ε_{A_L}, ε_{D_L}, … ε_{D_1} are defined by (2), denoting the energy of the sub-signals A_L, D_L, … D_1, respectively. The term ε_f is the energy of the original signal $f(t)$.

Note that (3) is not directly used as the feature vector. Instead, some sub-signals are selected and their percentages are calculated to form the feature vector. The selection is based on the following two criteria: 1) The sub-signals selected should be significant sub-signals contributing large energy percentages in $f(t)$. The reason for this criterion lies in the fact that the insignificant sub-signals generated by wavelet transform are normally contributing to noise and should be removed. Empirically, it is assumed that a sub-signal is significant if its ratio of energy contribution to the original signal is no less than 3%. 2) The sub-signals selected should be sensitive to the damage. Damage usually has different effects on different frequency bands. Hence different sub-signals have different sensitivities to damage. By selecting the sub-signals sensitive to the damage, it is guaranteed that the damage could be effectively captured. The sensitivity analysis can be derived either by finite element model analysis of the structure (analytical method) or by prior experiments (experimental method). For convenience, in this study only the significant sub-signals are chosen to form the feature vector.

Having chosen the energy percentage vector as the feature, the procedures for damage identification depend on the availability of the *a-priori* data. In an ‘unsupervised learning mode’, where data are only available from the undamaged structure, damage identification methods are based on feature comparison: two features, one extracted from the system in undamaged condition and the other from the current system, are compared in some way to obtain the damage indicator. The damage indicator is then compared to some threshold value and the conclusion about if the structure has deviated from the reference condition is obtained. On the other hand, in a ‘supervised learning mode’, where data from a system in different structural conditions (including the undamaged and some damaged conditions) are known in advance, the damage identification techniques are based on pattern classification: a database including models of the structure in different conditions is established using feature vectors for the *a-priori* data sets. Given a new data set which is to be classified as one of the conditions of the system, the task is to search through the database for the model which gives the best fit to the data. The corresponding condition of this database model is then applied to the data.

One problem remains to be resolved, which is the selection of the appropriate wavelet. The selection of a wavelet depends on the signal to be processed and on the particular application at hand. Taking an example of a 2-level wavelet analysis, Fig. 3 compares the shape and the frequency allocation property of the Haar wavelet with that of the db15 wavelet (one of the Daubechies’ wavelets). The irregularity of Haar wavelet causes a large overlap of the frequency allocation; on the contrary, wavelets like the db15 have longer support and are smoother, which could provide a much sharper division. This shaper division in frequency is preferred for the damage identification.

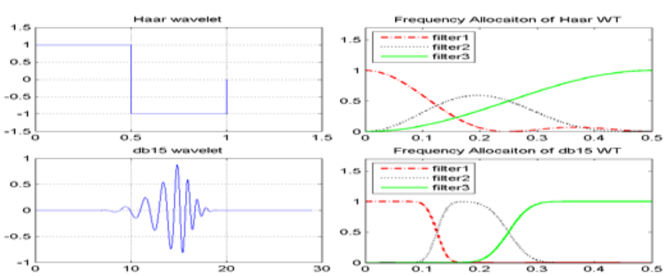

Fig. 3. Comparison of Haar Wavelet and db15 Wavelet.

IV. ANFIS-WPT Structural Damage Detection

A structural damage assessment method combining WPT with ANFIS is proposed in this section. This method is called ANFIS-WPT method. The procedures of the method include the following five steps: 1) Determine the architecture of the ANFIS. The architecture includes: a) the number of input variables, b) the number of linguistic values for each input variable, c) the type of MFs for each input linguistic value, d) the number of output variables, e) the number of linguistic values for each output variable, and f) the type of MFs for each output linguistic value. 2) Determine the rules for the ANFIS. 3) Prepare the training data sets (containing the input and desired output data pairs) for the ANFIS. 4) ANFIS training using the training data sets. 5) Pass the new data through the trained ANFIS and the damage information of the new data is obtained.

The steps above are detailed as follows. For convenience, it is assumed that data from a single sensor measurement are used. The number of all possible conditions for the system is $r+1$ (one healthy condition denoted as D_0 and r damaged conditions $D_1 \sim D_r$). For each condition, a total of N measurement data are available. This results altogether in $(r+1)\times N$ data sets and they are arranged as a data matrix:

$$Data \quad Matrix = \begin{bmatrix} \{y^{D_0-1}\}, & \{y^{D_0-2}\}, & \dots & \{y^{D_0-N}\} \\ \{y^{D_1-1}\}, & \{y^{D_1-2}\}, & \dots & \{y^{D_1-N}\} \\ . & . & . & . \\ . & . & . & . \\ \{y^{D_r-1}\}, & \{y^{D_r-2}\}, & \dots & \{y^{D_r-N}\} \end{bmatrix} \tag{4}$$

where $\{y^{D_j-i}\}$ ($i=1...N$, $j=0...r$) are output measurement data from the i^{th} test at condition D_j . Each row of the matrix contains all the available data sets for a certain condition.

Select a typical measurement signal $\{y\}$ in the data matrix (4) and perform WPT analysis on it. The original signal $\{y\}$ is decomposed into a number of sub-signals, from which p sub-signals are selected and the energy percentages of these sub-signals are calculated. In the current study, these energy percentages of the selected sub-signals are the inputs to the ANFIS model. Therefore, the number of input variables to the ANFIS is p . Three linguistic values characterised using linguistic terms as ‘small’, ‘medium’ and ‘large’ are defined for each of the p input variables. The type of these MFs for these linguistic values is ‘bell-shape’ and defined by:

$$\mu_s(x) = \frac{1}{1+|\dfrac{x-c_i}{a_i}|^{2b_i}} \tag{5}$$

There is only one output variable defined in the ANFIS: the structural condition. It is normally represented by a condition index for convenience. A zero-order Sugeno fuzzy model has been adopted in the ANFIS structure, which means that singleton values are defined for the output variable and the type of the corresponding MF is a distinct constant.

So far, only the architecture of the ANFIS model has been determined: It contains p inputs (corresponding to p energy percentages) and one output (condition index). Each input variable has ‘small’, ‘medium’ and ‘large’ linguistic values characterised by three bell-shape MFs. The number of ANFIS rules is determined by the combination of linguistic values for the input variables. For p input variables, each with three linguistic values, the number of resultant combinations is 3^p. Correspondingly, the number of rules is 3^p. For example, assume only two sub-signals are selected ($p = 2$). The two input variables and one output variable are denoted respectively as x_1, x_2 and z. For each input variable, three linguistic values denoted as { $M_1^{x_1}$, $M_2^{x_1}$, $M_3^{x_1}$ } (for x_1) and { $M_1^{x_2}$, $M_2^{x_2}$, $M_3^{x_2}$ } (for x_2) are defined. Therefore, a total of nine rules are contained in the ANFIS model:

Rule 1. If x_1 is $M_1^{x_1}$ *and* x_2 is $M_1^{x_2}$, then z is d_1

Rule 2. If x_1 is $M_1^{x_1}$ *and* x_2 is $M_2^{x_2}$, then z is d_2

Rule 3. If x_1 is $M_1^{x_1}$ *and* x_2 is $M_3^{x_2}$, then z is d_3

Rule 4. If x_1 is $M_2^{x_1}$ *and* x_2 is $M_1^{x_2}$, then z is d_4

....

Rule 9. If x_1 is $M_3^{x_1}$ and x_2 is $M_3^{x_2}$, then z is d_9

Having determined the ANFIS architecture and the rules, it is necessary to prepare data sets for training use. For each available output data $\{y^{D_j - i}\}$ ($i = 1...N$, $j = 0...r$) in the data matrix (4), perform the same WPT analysis as were done on the typical $\{y\}$ and the same p sub-signals are selected. Their energy percentages are arranged as a vector denoted as $Per^{D_j - i}$. This procedure is applied to all the data set in (4) and an Energy Percentage Matrix (EPM) is obtained:

$$EPM(WPT) = \begin{bmatrix} \{Per^{D_0-1}\}, & \{Per^{D_0-2}\}, & \ldots & \{Per^{D_0-N}\} \\ \{Per^{D_1-1}\}, & \{Per^{D_1-2}\}, & \ldots & \{Per^{D_1-N}\} \\ . & . & . & . \\ . & . & . & . \\ \{Per^{D_r-1}\}, & \{Per^{D_r-2}\}, & \ldots & \{Per^{D_r-N}\} \end{bmatrix} \quad (6)$$

The vector $\{Per^{D_j - i}\}$, containing p elements, is taken as an input vector for the ANFIS. Matrix (6) contains a total of $(r+1)\times N$ such input vectors for ANFIS. They are used as training data for ANFIS. The current ANFIS use a supervised learning algorithm, which means the target output for each input vector is needed. It has been mentioned that the output is the structural condition represented by a condition index. Depending on the level of damage assessment conducted, different output index patterns are adopted. If the ANFIS is used only to identify damage occurrence (level 1 damage assessment), the output indices are Boolean values (0 for healthy condition D_0, 1 for damaged cases $D_1 \sim D_r$). In this situation, the data matrix (6) contains a total of $(r+1)\times N$ input and desired output data pairs:

$$Data\ Matrix(Level\ \ 1) = \begin{bmatrix} \{Per^{D_0-1}, \ 0\}, & \{Per^{D_0-2}, \ 0\}, & \ldots & \{Per^{D_0-N}, \ 0\} \\ \{Per^{D_1-1}, \ 1\}, & \{Per^{D_1-2}, \ 1\}, & \ldots & \{Per^{D_1-N}, \ 1\} \\ . & . & . & . \\ . & . & . & . \\ \{Per^{D_r-1}, \ 1\}, & \{Per^{D_r-2}, \ 1\}, & \ldots & \{Per^{D_r-N}, \ 1\} \end{bmatrix} (7)$$

If the ANFIS is used for the damage localisation (level 2 damage assessment), a total of $r+1$ condition indices each corresponding to a structural condition need to be defined. Defining j as the index for condition D_j, the data matrix containing the input and desired output data pairs is:

$$Data\ Matrix(Level\ \ 2) = \begin{bmatrix} \{Per^{D_0-1}, \ 0\}, & \{Per^{D_0-2}, \ 0\}, & \ldots & \{Per^{D_0-N}, \ 0\} \\ \{Per^{D_1-1}, \ 1\}, & \{Per^{D_1-2}, \ 1\}, & \ldots & \{Per^{D_1-N}, \ 1\} \\ . & . & . & . \\ . & . & . & . \\ \{Per^{D_r-1}, \ r\}, & \{Per^{D_r-2}, \ r\}, & \ldots & \{Per^{D_r-N}, \ r\} \end{bmatrix} (8)$$

Data matrices (7) and (8), are used respectively for training ANFIS with two different levels of damage assessment.

The next step is ANFIS training. The number of the premise parameters to be determined is $3 \times 3 \times p$. This comes from the fact that for each of the p input variables, we use three MFs each decided by three premise parameters (*a*, *b* and *c* in (5)). The number of the consequent parameters to be determined is 3^p. The ANFIS architecture uses a hybrid learning algorithm [9] to estimate these $9p + 3^p$ premise parameters all together with the consequent parameters.

After the ANFIS model has been well trained, this ANFIS model can be used to find out the structure condition for new data. Given new data, the same WPT is performed and the same p sub-signals are selected. The energy percentages of these selected sub-signals are used as inputs to the trained ANFIS. The condition for the new data can be seen from the output (condition index) of the ANFIS.

So far, only the measurements from one sensor have been used. If there is more than one sensor, the method above is applied to each sensor separately and the final result for evaluating the condition of current data is the average of results from each ANFIS.

V. Application of The Proposed Approaches to a Cantilever Beam

In this research, an experimental study involving shaker-excited vibration tests of an aluminium cantilever beam was carried out in the laboratory. The beam is 90cm length and cross section 2.545 × 0.647cm. Zero-mean band-limited (0~500Hz) Gaussian white noise was used as the input signal to the amplifier. The amplifier gain was controlled manually and the shaker provided an approximately 10 N peak, via a random force input to the beam. A force gauge screwed on the bottom surface of the beam was used to directly measure the input. The shaker was attached with this force transducer through a stinger. Fig. 4 shows the experimental setup.

Six accelerometers (7g each) were screwed to the top surface along the centreline at selected positions (15cm, 30cm, 45cm, 60cm, 75cm, 90cm from the left fixed point, respectively). The data from each test came from these 6 accelerometers and 1 force transducer. The data were collected at a sampling rate of 10kHz for a duration of 4 seconds.

Five damage scenarios (E1~E5) were simulated by adding a lumped mass (22g) at 30cm, 45cm, 60cm, 75cm, and 90cm, respectively (see Fig. 4.). A summary of the experimental damage conditions is provided in Table 1

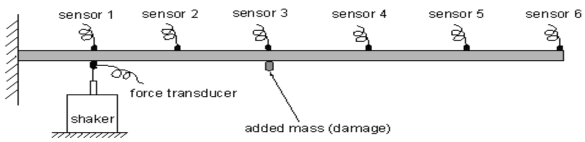

Fig. 4. Cantilever beam for experiment

TABLE I
SUMMARY OF DAMAGE CASE E1~E5

Damage Case	Location of Damage	Damage Description
E1	30cm	adding a lumped mass of 22g
E2	45cm	adding a lumped mass of 22g
E3	60cm	adding a lumped mass of 22g
E4	75cm	adding a lumped mass of 22g
E5	90cm	adding a lumped mass of 22g

A. *ANFIS-WPT results*

The experiment was repeatedly carried out under each of the six possible conditions of the system. The system response data and the corresponding condition were recorded during the test. From each condition, 20 test data are used, within which the first 10 are for the training use and the remaining 10 are for the testing use. Therefore, altogether there are available 60 training data sets and 60 test data sets.

The response data are not used directly in the ANFIS model. Wavelet-based transforms are carried out first on these data. In the proposed ANFIS-WPT method, each response signal is applied by the five-level db15 WPT (db15 wavelet is adopted in this study for the reasons described at the end of section III). The signal is then decomposed into 32 sub-signals, from which three sub-signals are selected. These three energy percentages are taken as the three input variables for the ANFIS model.

The ANFIS used here contains 27 rules, with three bell-shape MFs assigned to each input variable. The total number of parameters is 54, including 27 premise parameters and 27 consequent parameters.

ANFIS is used for the purpose of structural damage identification. However, there are various levels of damage assessments. Two ANFIS models, ANFIS1 and ANFIS2 are established accordingly. ANFIS1 is used to identify damage occurrence (level 1 damage assessment) while ANFIS2 is used for damage localisation (level 2 damage assessment). The architecture of these two ANFIS models is the same, but they produce different output values. ANFIS1 is only used to distinguish healthy and damaged conditions; therefore the output is a Boolean value (0 for healthy, 1 for damaged). The output of ANFIS2 needs to differentiate all the possible conditions and hence is a little more complicated. One option is to define it as a numerical value j ($j = 0 \sim 5$), where j corresponds to condition D_j .

Applying WPT on the 60 training data sets, 60 training input sets each containing three input values are obtained. The target output data is the corresponding condition (Boolean values for ANFIS1 model and 0~5 for ANFIS2). These 60 input and desired output data pairs are used to train the ANFIS model. For ANFIS1 models, the training process stopped when the number of iterations reached 200. For ANFIS2 models, the training process stopped when the number of iterations reached 500.

After the two ANFIS models are trained, the testing data are used for verifying the identified ANFIS models. If the proposed method is effective, then these ANFIS models should be able to classify the testing data set to the right condition.

Note that in the ANFIS-WPT method, the information from each sensor is used separately. Each of the six sensors corresponds to an ANFIS model. The six ANFIS models for level 1 damage assessment are denoted as ANFIS1-Sensor1, ANFIS1-Sensor2· · ·ANFIS1-Sensor6 for convenience. The six ANFIS models for level 2 damage assessment are defined in a similar way as ANFIS2-Sensor1· · ·ANFIS2-Sensor6.

Fig. 5 illustrates the MFs of ANFIS1-Sensor1 model before and after training. Notice that two MFs of the first input variable have been changed significantly after training.

Fig. 6 shows the ability of the six trained ANFIS1 models in identifying damage occurrence when evaluated by the testing data. The residual shows the difference between the expected output (real condition index) and the actual output from ANFIS model. The ‘ *rms* ’ is root mean square of the residual sequences and is used as a criterion for testing error. It can be seen that, no matter what the chosen sensor is, the proposed method can successfully classify all the conditions.

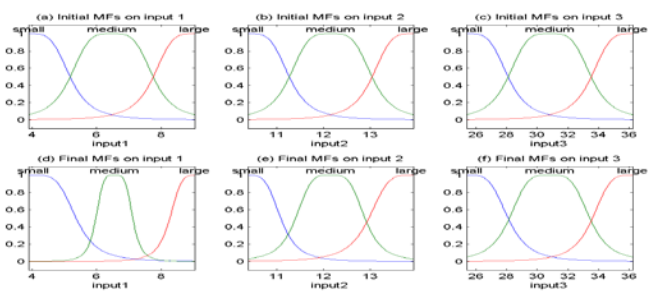

Fig. 5. Initial and final MFs for three input variables (ANFIS1-Sensor1, ANFIS-WPT method).

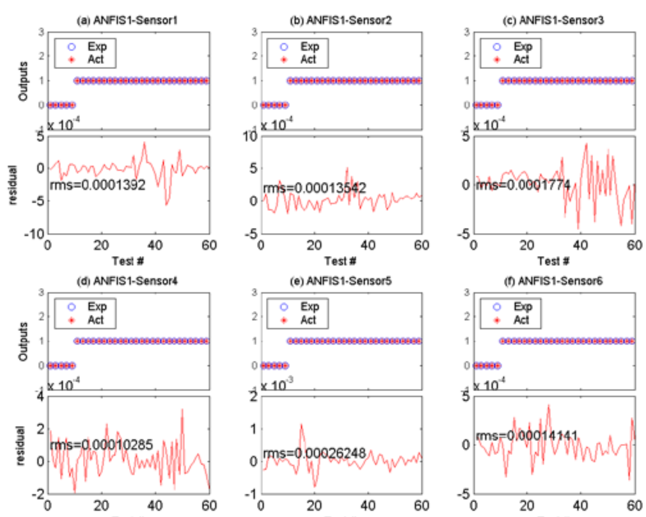

Fig. 6. Testing results and the corresponding error curves (ANFIS1, ANFIS-WPT method, using 6 sensors separately)

Fig. 7 shows the ability of the six trained ANFIS2 models in identifying damage locations when evaluated by the testing data. It can be seen that all the ANFIS models perform well and can successfully classify the input data to the right condition. However, the testing error is increased compared with Fig. 6. This is not surprising because the current six ANFIS2 models are required to define more associations than the previous

ANFIS1 models. The larger testing error is caused by the complexity accompanied with damage localisation.

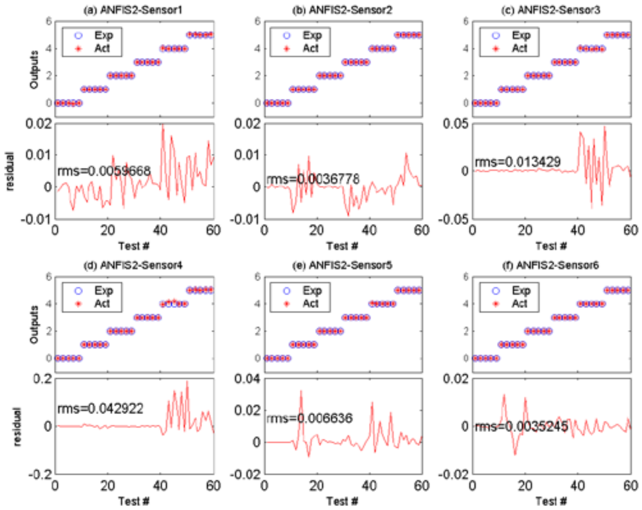

Fig. 7. Testing results and the corresponding error curves (ANFIS2, ANFIS-WPT method, using 6 sensors separately).

VI. Conclusion

In this paper, an approach to structural damage detection combining ANFIS and WPT has been introduced. The structural vibration response signal is decomposed by the WPT into a number of sub-signals, from which some are selected based on their energy percentages. The energy percentages of the selected signals are taken as inputs to the ANFIS model. The output of the ANFIS is a condition index, which can be a Boolean value (0 or 1) for level 1 damage assessment use, or a number of values for level 2 damage assessment use. Provided an ANFIS model is well-trained by the available data, it can be used for health monitoring and damage localisation. The proposed method has been applied to the data from a cantilever beam for damage detection and localisation. The testing result shows that the method is successful in detecting and localising damage. Therefore, the proposed damage assessment methodology of combining ANFIS with wavelet transform has great potential in structural health monitoring systems (monitoring systems which are able to interrogate sensor measurements autonomously for indications of structural damage).

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VIII. Biography

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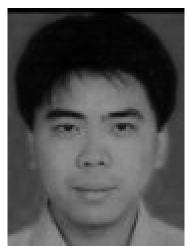

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