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ART-based multiple neural networks for monitoring offshore platforms

Lalu Mangal, V. G. Idichandy & C. Ganapathy

Ocean Engineering Centre, Indian Institute of Technology, Madras, India

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A novel scheme using artificial neural networks to automate the vibration monitoring method of detecting the occurrence and location of damage in offshore jacket platforms is presented. A multiple neural network system is adopted which enables the problem to be decomposed into smaller ones, facilitating easier solution. An adaptive resonance theory (ART) neural network is used for damage diagnosis and its advantages and limitations are investigated. A comparison between a back-propagation network and an ART network is presented. The adaptability of ART for on-line monitoring is explored for possible adaptation to monitor offshore platforms in service. The system developed is tested using data from a finite-element analysis of a scale model of a jacket platform. Copyright © 1996 Elsevier Science Limited.

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1 INTRODUCTION

The discovery of large oilfields in deeper waters has necessitated the construction of offshore structures in greater depths of water. A typical offshore structure used for oil and gas production encounters larger forces due to wind and currents than comparable land structures. In addition it will be subjected to higher levels of cyclic load due to gravity waves causing fatigue damage. These types of structure also have to withstand stresses due to self weight and water pressure. Since they are constructed in harsh environments, long-term damage also takes place due to corrosion, erosion and scour. Offshore structures are also prone to short-term damage which can be attributed to loads which exceed the design load, for example unprecedented severe storms, sea quakes or accidental collisions with supply vessels. Damage of all kinds should be detected quickly so that corrective action can be taken to avoid catastrophic failures. Consequently, there is a need for an efficient and reliable monitoring system for such structures.

The methods currently adopted for monitoring offshore platforms are visual inspection, measurement of strains, monitoring of dynamic parameters, detection of flooding in members, and local damage detection using acoustic and magnetic methods. Visual inspection, although efficient in the case of land structures, is difficult in offshore structures in deeper waters. Marine growth also prevents the use of this method. Acoustic and magnetic methods are very costly and are not capable of detecting global damage. The measurement of dynamic parameters has been proved to be efficient for detection of local as well as global damage.[1–4] This method also has the advantage of continuous monitoring and automatic detection in addition to being independent of expensive diver support. Information processing systems like neural networks are useful in the implementation of automated structural health monitoring.[5–8]

The identification of damage of the members of a structure from response characteristics is an inverse process. As a first step, a suitable mathematical model is constructed. Different representative cases of damage are induced in the mathematical model and the corresponding dynamic parameters are determined. These are compared with the measured dynamic parameters of the structure. The damage of the structure, if any, will correspond to the pattern which most closely resembles the input pattern. Manual comparison of the pattern becomes impossible as the number of damage cases increases. To overcome this difficulty, the pattern matching capability of neural networks is employed.

In the present work, the problem is broken into several subproblems and different neural networks are used to solve each of these problems. A comparison between an adaptive resonance theory (ART) network and a back-propagation network (BPN), with special reference to the present problem, is presented. The applicability of an ART network to online damage detection is investigated. Finally, the developed system is tested using a large number of damage cases to bring out its feasibility and limitations.

2 NEURAL NETWORKS

The intensive research which has taken place recently in the field of artificial intelligence has made it possible to solve badly structured problems which were not amenable to conventional programming techniques. The artificial neural network, or simply the neural network, is one of the outcomes of this research. They are information-processing systems loosely modelled on the working of the human brain. They attempt to achieve better performance by using a massively parallel architecture. Neural networks have a greater degree of robustness or fault tolerance than conventional methods. They also have adaptive learning capabilities analogous to human beings. A neural network consists of a number of interconnected simple processing units called artificial neurons which are capable of only simple mathematical operations. Before any neural network is put into operation, it should be properly trained. Training a neural network means adjusting the values of the internal parameters such that for a set of input data, the desired set of outputs is obtained. There are two classes of training methods, *viz* supervised and unsupervised. Some of the commonly used neural network paradigms are back propagation, the Hopfield net, counter propagation, adaptive resonance theory, and bidirectional associative memory. The two paradigms used in the present work, *viz* the back propagation network (BPN) and adaptive resonance theory (ART) are briefly described below. For more details, the reader should refer to the standard literature.[9–12]

3 BACK PROPAGATION NETWORKS

Back propagation[13] is a very popular and commonly used neural network paradigm. It uses a multi-layer feed-forward network (Fig. 1). This type of network, with at least two hidden layers, has been shown to be capable of representing any complex input–output relation. The algorithm gives a method for training any feed-forward network to learn a set of input–output pairs. The method is briefly described below.

The multi-layer feed-forward network consists of different interconnected layers of artificial neurons (Fig. 2). The first layer is the input layer where the inputs are applied and the last layer is the output layer. The layers in between the input and output layers are termed hidden layers. The activity of a neuron, x_i, is the sum of the inputs from the different connecting pathways, which is the incoming signal u_j multiplied by the weight w_{ij} of

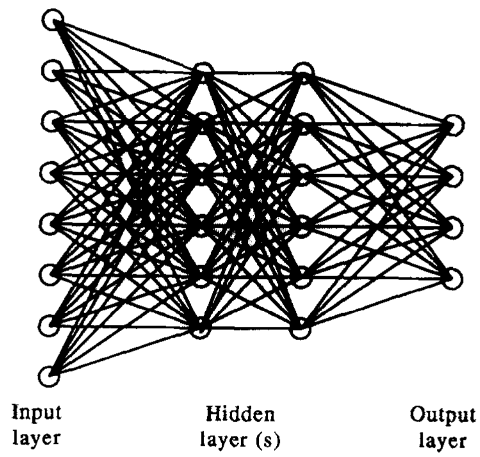

Fig. 1. Multi-layer feed-forward network.

that pathway, i.e.

$$x_i = \sum (w_{ij} \times u_j) \quad (1)$$

The outgoing signal, S_i, from a particular neuron i is the value of the squashing function of the activity in that neuron given by

$$S_i = f(x_i) \quad (2)$$

The squashing functions can be hard limiters, sigmoid, or hyperbolic tan functions. The inputs are summed up and the squashing function is applied at each neuron before passing to the next layer. The process is repeated at each layer in the forward direction until the output layer is reached.

The basis of the BPN training algorithm is simply the gradient descent method. The error at the output layer, i.e. the difference between the output obtained S_i and the desired output D_i is propagated back through the network and the weights are adjusted using the formula

$$\Delta w_{ij} = \eta \sum (\delta_{\text{output}} \times u_{\text{input}}) \quad (3)$$

where

$$\delta_{\text{output}} = f'(x_i) \times (D_i - S_i) \quad (4)$$

Here, input and output refer to the two ends i and j of the connection concerned and u stands for the appropriate input activation from a hidden unit or a real input. $f'(x_i)$ is the first derivative of the squashing function applied to x_i and η is a constant termed as the learning rate.

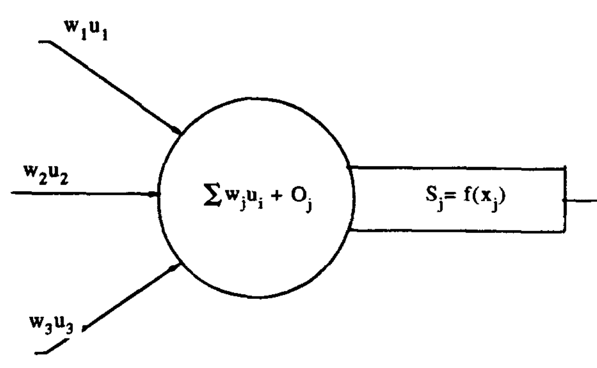

Fig. 2. Artificial neuron.

The BPN has been successfully employed in a wide variety of problems such as speech recognition and object identification. BPNs are very robust and can represent any highly nonlinear input–output relationship. Their main disadvantage is the long uncertain training process. The possibility of the network converging to a local minima is high. Also, it is difficult to incorporate adaptive learning capabilities.

4 ADAPTIVE RESONANCE THEORY

An adaptive resonance theory network for analogue data (ART-2) has been proposed by Carpenter & Grossberg.[14] Often in common neural network paradigms, learning a new pattern erases the previous training. ART networks have the capability to learn new data or adapt themselves to new situations. The ART network is a vector classifier. It accepts an input vector and classifies it into categories depending upon their similarities. If the input pattern does not match any one of the stored patterns, within a given tolerance limit (the vigilance parameter), a new class is created. Otherwise, the stored pattern which matches the new pattern is adjusted to look more like the new pattern. The operation of a simplified version of the ART network is described below.

The main components of ART systems are the comparison layer, the recognition layer, gain control and the reset mechanism (Fig. 3). The nodes on the comparison and recognition layers are fully interconnected. Initially, the pattern is presented to the comparison layer. The net activity of the comparison layer is the sum of the input vector, input from the gain control, and any feedback from the recognition layer. This is propagated to the recognition layer through the bottom-up weights. The recognition layer acts in a winner-takes-all manner. Only one node in the recognition layer is activated. This is propagated back to the comparison layer through the top-down weights where it is compared with the input vector. If both match within the given vigilance tolerance, then the input vector is classified as the class corresponding to the winner in the recognition layer. If the patterns do not match, then a reset signal is sent to the recognition layer to disable the winning node so that it does not take part in the competition during the next pass. This process is repeated until a match is obtained for the input pattern or all the nodes in the recognition layer are exhausted. In this case, a new node is selected and the pattern is classified as a new class by adjusting the corresponding weights.

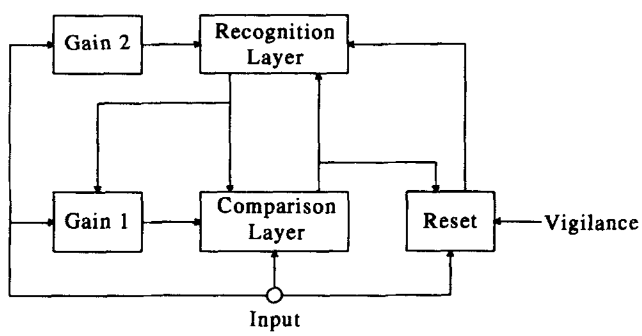

Fig. 3. Adaptive resonance theory network.

ART has been successfully used for classification problems. The main advantage of ART is its ability to learn new patterns without losing previously trained patterns. Also, ART takes much less time for training compared with BPNs.

5 PRINCIPLE

The vibration monitoring idea is adopted in this work. The basic principle is that for any structure, the natural modes of vibration, which are its fundamental characteristics, are independent of the environmental forces and do not change unless there are changes in stiffness or mass distribution. Vibration monitoring consists of determination of the dynamic parameters of the structure *viz* natural frequencies and mode shapes. Any change in the mass or stiffness distribution causes changes in the dynamic parameters. These changes may be due to damage in members, changes in deck mass, accumulation of marine growth, or foundation scour. It has been demonstrated that integrity monitoring based on frequency shift alone is not feasible for jacket platforms.[15] Changes in frequency may be caused due to variations in deck mass or due to excessive marine growth. However, a monitoring system should be able to identify these changes since it has to be ensured that the changes are not due to any damage. Consequently, it is desirable to use both frequency and mode shape for monitoring.

As has been already stated, neural networks are used for identification of member damage from response characteristics. It has been observed that if a single neural network is used, the identification process is not efficient. This is due to the fact that the range of mode shape values are widely different for different modes and the changes may go undetected. Hence, the strategy adopted here is to train a set of neural networks to identify the damage in members and changes in deck mass, and use these networks to monitor the state of the structure. The inputs to the networks are the modal vectors and natural frequencies. In the present work, the problem is decomposed into several subproblems and different neural networks are used to solve each of the problems. Since the problem size is reduced, the training time is considerably reduced and the efficiency of the system is increased. The input data used for each neural network are different. For example, the input data for the network used for detecting the changes in deck mass are the natural frequencies of the structure, whereas the modal vectors are used as inputs to the networks for detecting damage. Data obtained analytically using the finite-element method are used for training the networks. The networks used for detecting the damage are trained by several sets of data obtained with different deck masses to eliminate the effect of deck mass variation. Similarly, the networks used for

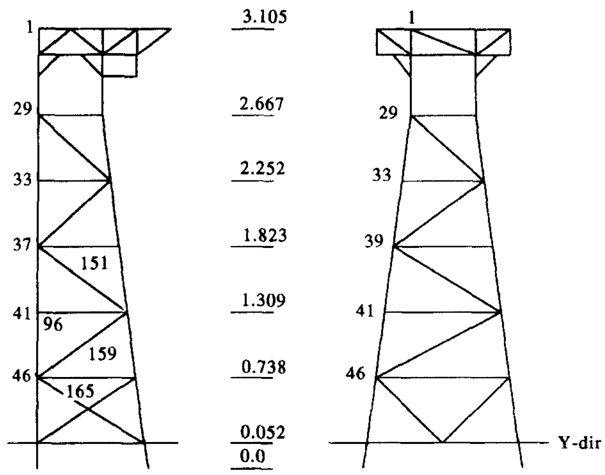

Fig. 4. Different views of the jacket platform model.

detecting the deck mass are trained using several sets of data for different amounts of damage.

6 IMPLEMENTATION

A scale model of a typical offshore platform was used for the present study (Fig. 4). The model has a scale factor of 1:35 and was fabricated using PVC tubes. Finite-element analyses were done on the model to generate the data for training the networks, as well as to test it. For the training data, 12 cases were analysed (Table 1). The schematic view of the multiple neural network system devised is shown in Fig. 5. The first neural network is used to detect the changes in deck mass. Since this network is used to define an input–output relationship, it is implemented using a BPN only. The output from this network is a single value which is related to the deck mass. The network was trained using data for −10, 0 and +10% changes in deck mass. All the damage cases were used for training such that, altogether, there were five sets of training data (including that for the undamaged case). Neural net 2 uses data for the second flexural mode in the x-direction to detect damage in members 159 and 151. Neural net 3 uses the second mode in the y-direction to detect damages in members 159 and 165. There is no appreciable change in the first few modes due to damage in member 96, but there is a significant change in the 14th mode. Hence neural net 4 uses data for the 14th mode in the x-direction to detect damage in member 96. Neural nets 2, 3 and 4 were implemented using both BPNs and the ART2 algorithm. A three-layer BPN was used for the present study. The parameters of each BPN were different and were chosen to get the best performance. The vigilance parameter for each ART network which gave the best result was used. These networks were trained using the data for different deck masses such that there were three sets of training data for each network.

Table 1. Data sets used for training the networks

Damage case	Deck mass −10%	Deck mass 0%	Deck mass +10%
Undamaged	x	x	x
Member 159 damaged	x	x	x
Member 165 damaged	x	x	x
Member 151 damaged	x	x	x
Member 96 damaged	x	x	x

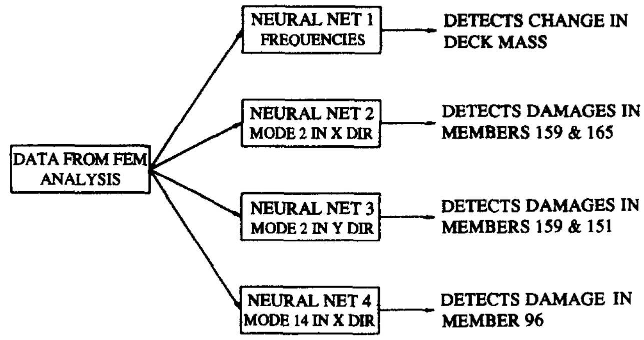

Fig. 5. Schematic view of the multiple neural network system.

7 RESULTS

The system developed was tested using different damage cases with varying deck masses. All cases used for testing the system were different from those used for training. Damage induced simultaneously in two members was also used to explore the suitability for detecting combined damage. The system was also tested with some cases of partial damage. The damage cases used for testing the outputs from BPNs and the ART networks are given in Tables 2–5. The output vector for the BPN corresponding to the damage case is also given in the tables. Cut-off values of 0.2 for the lower limit and 0.8 for the upper limit are used for inference from the BPN output.

The first network, a BPN, was found to give fairly good estimates of the changes in deck mass (Table 2). The maximum error was 2.02%, which occurred for the combined damage case. This shows that damage in the members does not seriously affect the assessment of deck mass. This can be attributed to the fact that the natural frequencies, which are used as the input to the network are fairly insensitive to damage.

Table 2. Outputs from first network

Testing cases	Output from network	Required output
Members 159 and 165 damaged, deck mass 0%	2.023%	0%
Member 159 damaged, deck mass +5%	5.299%	5%
Member 165 damaged, deck mass −15%	−14.150%	−15%
Member 159 damaged, deck mass +15%	+13.870%	+15%
Member 151 damaged, deck mass −5%	−3.998%	−5%

Table 3. Outputs from the second network

Sl No.	Damage case	Back-propagation		ART-2 output
		Output obtained	Correct output	
1	Members 151 and 165 damaged	0.958, 0.000, 0.213*	0, 0, 1	Unknown pattern*
2	Members 151 and 96 damaged	0.000, 0.000, 0.888	0, 0, 1	Member 151 damaged
3	Members 159 and 165 damaged	0.000, 0.981, 0.011	0, 1, 0	Member 159 damaged
4	Members 159 and 96 damaged	0.000, 0.992, 0.088	0, 1, 0	Unknown pattern*
5	Member 159 damaged, deck mass +5%	0.000, 0.994, 0.049	0, 1, 0	Member 159 damaged
6	Member 159 damaged, deck mass −15%	0.000, 0.995, 0.042	0, 1, 0	Member 159 damaged
7	Member 165 damaged, deck mass −15%	0.999, 0.000, 0.007†	Unknown	Member 159 damaged
8	Member 159 damaged, deck mass +15%	0.000, 0.993, 0.052	0, 1, 0	Member 159 damaged
9	Member 151 damaged, deck mass −5%	0.009, 0.000, 0.898	0, 0, 1	Member 151 damaged
10	Member 151 partially damaged(90%)	0.665, 0.000, 0.606*	0, 0, 1	Unknown pattern*
11	Member 151 partially damaged(80%)	0.943, 0.000, 0.384*	0, 0, 1	Unknown pattern*

* Detects, cannot identify.
† Does not detect.
‡ Incorrect diagnosis.

The outputs from the other networks are grouped into four classes *viz* one which gives the correct diagnosis, one which does not detect the damage (marked †), one which detects but cannot identify the damage (marked *) and one which gives an incorrect diagnosis (marked ‡). Out of the 26 test cases, only one (No. 7 from ART2 network 2) gave an incorrect output. This may be attributed to the fact that network 2 is not trained to detect damage in member 165 and the patterns for damage to members 159 and 165 are similar. But the same damage is properly identified by net 3. Damage with the deck mass changed is properly diagnosed. This establishes that the system is insensitive to changes in deck mass. Most of the combined damage is properly identified by the system, but it fails to identify partial damage, as

Table 4. Output from third network

Sl No.	Damage case	Back-propagation		ART output
		Output obtained	Correct output	
1	Members 151 and 165 damaged	0.776, 0.000, 0.998*	0, 0, 1	Unknown pattern*
2	Members 151 and 96 damaged	0.975, 0.000, 0.998*	Unknown	Unknown pattern
3	Members 159 and 165 damaged	0.000, 0.982, 0.979*	0, 1, 0/0, 0, 1	Member 165 damaged
4	Members 159 and 96 damaged	0.000, 0.988, 0.580*	0, 1, 0	Member 159 damaged
5	Member 159 damaged, deck mass +5%	0.000, 0.989, 0.183	0, 1, 0	Member 159 damaged
6	Member 159 damaged, deck mass −15%	0.000, 0.991, 0.224*	0, 1, 0	Member 159 damaged
7	Member 165 damaged, deck mass −15%	0.006, 0.134, 0.968	0, 0, 1	Member 165 damaged
8	Member 159 damaged, deck mass +15%	0.000, 0.988, 0.164	0, 1, 0	Member 159 damaged
9	Member 151 damaged, deck mass −5%	0.982, 0.000, 0.002†	Unknown	Unknown pattern
10	Member 165 partially damaged(90%)	0.340, 0.000, 0.884*	0, 0, 1	Member 165 damaged
11	Member 165 partially damaged(80%)	0.912, 0.000, 0.745*	0, 0, 1	Unknown pattern*

* Detects, cannot identify.
† Does not detect.
‡ Incorrect diagnosis.

Table 5. **Output from fourth network**

Sl No.	Damage case	Back-propagation		ART-2 output
		Output obtained	Correct output	
1	Members 151 and 96 damaged	0.040, 0.959	0, 1	Member 96 damaged
2	Members 165 and 96 damaged	0.077, 0.922	0, 1	Member 96 damaged
3	Member 96 partially damaged (90%)	0.991, 0.008†	0, 1	Unknown pattern*
4	Member 96 partially damaged (80%)	0.972, 0.271*	0, 1	Undamaged†

* Detects, cannot identify.
† Does not detect.

can be observed from the outputs. Only one case out of six of partial damage is diagnosed. Another interesting result is the output of the BPN for combined damage in members 159 and 165 (No. 3 in network 2). The output obtained is the sum of the required outputs for damages cases 159 and 165, but this is classified as inconclusive here. Finally, it can be observed that the damage cases which are identified as undamaged by the system are very few.

8 COMPARISON BETWEEN BPNS AND ART

As already stated, the BPN, once trained, cannot adapt itself to new situations. But an ART network can adapt itself to changed conditions and new situations. The ART2 network program developed for the present system is capable of operating in the following modes.

8.1 Training mode

In this mode, the system automatically classifies the given patterns depending upon the vigilance parameter given and uses an iterative slow learning method to adjust the weights to the centroidal pattern of each class. Identification notes can be given for each class by the user.

8.2 Adaptive operational mode

The network keeps on accepting inputs from a system and uses the slow learning technique to adapt itself to slow changes. Slow changes, like accumulation of marine growth, etc. will not be detected. However, sudden changes will be detected.

8.3 Non-adaptive operational mode

Here, no adaptation or learning is done. The system remains stable and when the input pattern does not match the trained cases, a warning is given. This mode is also capable of detecting slow changes.

These three modes are very useful in online monitoring systems for offshore platforms. ART systems can also be used with different vigilance parameters such that even small changes can be detected although identification may not be possible. ART can also be used for unattended monitoring systems such that any unrecognised pattern encountered can automatically be tagged as a new class by storing the date and time of its occurrence facilitating the analysis at a later stage.

As for the detection of damage, both BPNs and ART give good results. For partial damage, only ART gives a correct diagnosis. ART is observed to be more stringent since the cases of unknown damage which are diagnosed as undamaged by the BPN are classified as unknown damage by ART. ART is a vector classifier and hence could not be used for the assessment of deck mass. Hence, it is advisable to use both BPNs and ART simultaneously for good results.

9 CONCLUDING REMARKS

1. A multiple neural network for damage diagnosis of a jacket platform model was presented.
2. ART networks were used for damage detection and their feasibility for online damage detection was established.
3. A comparison of ART and BPNs was carried out with special reference to the present application.
4. It is suggested that for better performance, both ART networks and BPNs are to be used simultaneously.
5. Further work is required to develop a system to integrate the two types of network and to infer the correct diagnosis from their output.

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