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Vibration Based - Crack Detection in Simplified Wind Turbine Blades Using Artificial Neural Networks

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ABSTRACT:

Wind turbine blades are complicated components for inspection by non-destructive techniques because they are multi-layered, have variable thickness and are made of anisotropic materials. This paper proposes the use of Artificial Neural Networks (ANN) for the detection of crack location and crack depth in wind turbine blades. Wind turbine blade is approximated by a laminated composite, cantilever tapered beam with a transverse open surface crack. The natural frequencies which are influenced by crack specifications are obtained by a Finite Element Method (FEM) via ANSYS software. Experimental setup has been developed to validate the results obtained from the finite element software ANSYS. The numerical data obtained from (FEM) are then used to train a feed-forward back propagation neural network using Matlab environment. The input parameters to the neural network are the first three relative natural frequencies, while the output parameters are the relative crack depth and relative crack location. Simulations are carried out to test the performance and the accuracy of the trained network by comparing the results for the crack depth and crack location obtained from (ANN) with those obtained from (FEM). The simulation results show that the proposed Artificial Neural Network can precisely detect the crack location and crack depth.

Keywords: Crack detection, Wind turbine blade, Composite beam, Neural network.

أستخدام أساسيات ألأهتزازات في الكشف عن الشقوق في شفرات توربين الرياح بتقنية الشبكات العصبيه الأصطناعيه

الخلاصة

أن أستخدام التقنيات اللاأتلافيه لفحص شفرات توربينات الرياح يعد معقدا للغايه لكون هذه الشفرات متعددة الطبقات ، ولها سمك متغير ومصنوعه من مواد ذات خواص متباينه. يقترح البحث الحالي استخدام الشبكات العصبيه الأصطناعيه في الكشف عن موقع وحجم الشقوق في شفرات

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توربينات الرياح . تم في هذا البحث تمثيل الشفره بعتبه كابوليه مستدقه ومصنوعه من مواد متراكبه متعددة الطبقات و تحتوي على شق عرضي مفتوح . تم الحصول على الترددات الطبيعيه للشفره التي تتأثر بطبيعة الشق من خلال طريقة العناصر المحدده باستخدام البرنامج (ANSYS) والتي تم التحقق من صحتها عمليا .وتم أستخدام البيانات العدديه المستحصله من طريقة العناصر المحدده في تدريب الشبكه العصبيه ذات التغذيه الأماميه من خلال بيئة الماتلاب. ان متغيرات الأدخال للشبكه العصبيه هي أول ثلاث ترددات طبيعيه للشفره بيمنا تكون مخرجات الشبكه العصبيه هي الموقع والعمق النسبي للشق المناظره لتلك الترددات المدخله. تم تنفيذ عملية محاكاة لأختبار أداء ودقة الشبكه العصبيه المقترحه من خلال مقارنة النتائج المستحصله من الشبكه العصبيه مع تلك المستحصله من خلال طريقة العناصر المحدده.أثبت نتائج المحاكاة بأن الشبكه العصبيه الأصطناعيه المقترحه قادره على كشف موقع وعمق الشق بدقه عاليه.

INTRODUCTION

One of the essential components in wind turbines are their blades. Blade failure is very costly because it can damage other blades, the wind turbine itself or the other wind turbines located in neighbor. Efficient non-destructive testing (NDT) techniques will extend wind turbine life and reduce failure possibility [1]. Many attempts in recent years have been made to deal with damage detection in wind turbine blades. Inspection methods based on ultrasonic scanning, X-rays, and infrared thermography have many drawbacks [2-5]. One of these drawbacks is the high cost of this equipment. These methods also require highly skilled and trained operators with years of experience. A further disadvantage of methods such as X-rays, ultrasonic scanning etc, is the fact that defects may be overlooked due to shielding by the structure itself.

Recent studies have introduced vibration – based damage detection methods for wind turbine blades as an alternative effective methods [6- 8].These methods have been proved as fast and inexpensive means for crack detection. The basic idea behind this technology is based on the fact that a crack in a structure induces local flexibility which affects the dynamic behavior of the whole structure to a considerable degree. It results in reduction of natural frequencies and changes in mode shapes. An analysis of these changes makes it possible to determine the location and depth of cracks.

The aim of this paper is to use the vibration-based analysis and Artificial Neural Networks to detect the transverse crack specifications (location and depth) in wind turbine blades, considering the complicated structure of the wind turbine blades. The input parameters to the neural network are the first three relative natural frequencies, while the output parameters are the relative crack depth and relative crack location. In order to train the neural networks successfully, many actual sets of input-output data are required. It is extremely difficult and time-consuming to produce large enough training data sets from experiments. Hence, the actual data are obtained using Finite Element Method via ANSYS software for different crack location and depth. Experimental setup has been developed to validate the results obtained from the finite element software ANSYS. The neural networks are then trained by means of feed-forward back propagation method using Matlab environment. Some new untrained crack specifications are used as network inputs to test the performance of the neural networks. The test results show that the proposed neural networks are able to predict the crack specifications with high accuracy.

Geometric and Material Modeling of Specimens

Wind turbine blades are complicated components for inspection by non - destructive techniques: they are multi -layered, have variable thickness and are made of anisotropic materials. Wind turbine blades are made mainly of GFRP (glass fiber reinforced plastic) composite layers joined together by epoxy glue [1]. A wind turbine blade can be seen as a laminated tapered beam of finite length with aerofoil profile as cross-sections. A rectangular section representing a cross-section of the blade can give qualitatively appropriate results in a simpler way [9, 10]. Such a model has been adopted for the present analysis. In this paper, the specimen of the wind turbine blade has been approximated by a laminated composite tapered beam made of (0/90) woven E-glass fiber and epoxy resin using hand lay-up process. The geometrical dimensions of the wind turbine blade specimen are shown in Figure (1). The mechanical properties for fiber and matrix are presented in Table (1). The elastic properties of the composite material were calculated analytically using the simple rule of mixtures given in [11].

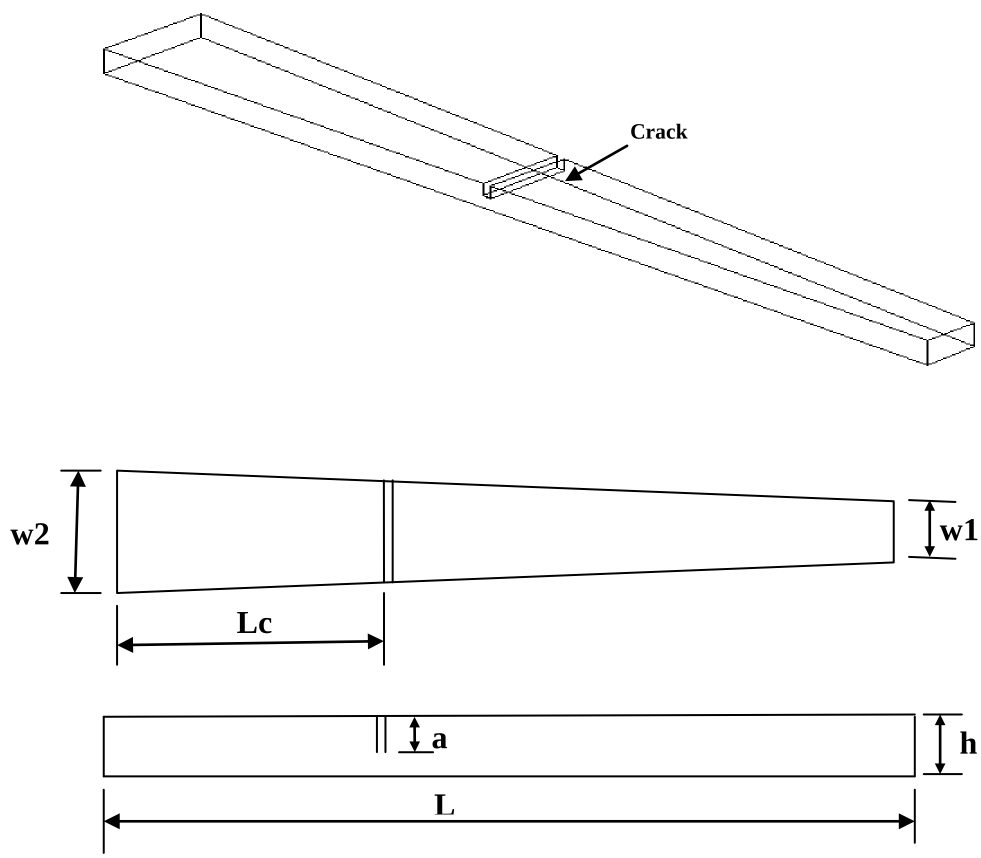

Figure (1): Geometry of the wind turbine blade with a transverse crack.

Table (1): Mechanical properties of fiber and matrix.

Material	Properties	Value
Glass fiber	Elasticity Modulus (GPa)	74
	Shear Modulus (GPa)	29.6
	Density ($kg/m^{3)}$	2500
	Poisson's ratio	0.25
Epoxy resin	Elasticity Modulus (GPa)	4
	Shear Modulus (GPa)	1.43
	Density ($kg/m^{3)}$	1100
	Poisson's ratio	0.4

EXPERIMENTAL SET-UP

The composite tapered beams under test are made of cross ply 10 - layered (0/90) E-glass fibers embedded in an epoxy matrix with fiber volume fraction (44%). The test specimens in the present experimental work, have an overall laminate thickness h = 10 mm and laminate density ρ=1716 kg/m^3. The thickness of each ply is 1 mm. The blade chord at the tip section and root section are w1= 30 mm and w2= 60 mm respectively. When the blade is clamped as a cantilever configuration, the specimen has a free length of L =500 mm. Transverse cracks can occur in wind turbine blades when a single or multi-ply fails. In this work, a transverse open crack was artificially generated by means of a thin saw cut (around 1.2 mm width). The depth of crack will be equal to the number of plies failed multiplied by the thickness of each ply. It is assumed that the crack extends throughout the width of the beam; this is because the wind turbine blades are loaded whole width (chord). This induces stresses along the width. Hence, the lamina can fail completely along the chord of the blade. Experiments are conducted to determine the natural frequencies on four specimen blades having same geometry and material as shown in Figure (2). A transverse crack has been generated at a length L_C = 100 mm ,200 mm,300 mm and 400 mm from the fixed end by varying crack depth of a = 1 mm , 3 mm and 5 mm deep at each location, which correspond to one, three and five plies failure respectively. The pictorial view of the complete experimental setup is shown in Figure (3). The laminated composite tapered beam is rigidly clamped at the large end (root) with a fixture bolted by means of T-bolts. The free end of the cantilever beam is excited with vibration exciter driven by a function generator connected to a power amplifier. A digital storage oscilloscope is connected to observe the vibration response of cracked cantilever beam after getting the signal from an accelerometer glued at the tip of the beam. The natural frequencies are measured from the function generator at the point of resonance under the excitation.

Figure (2): Laminated tapered beam specimens.

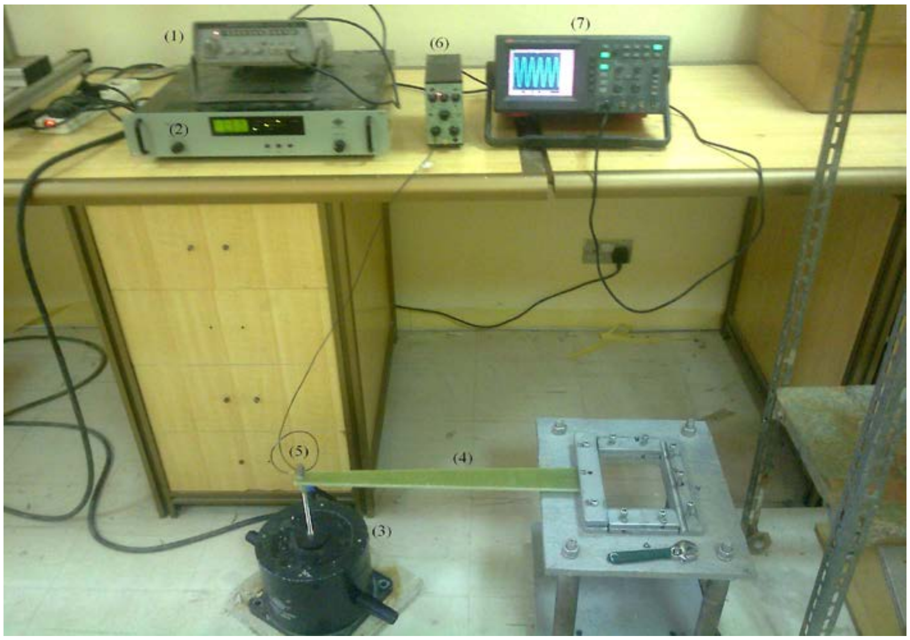

Figure (3): Experimental set up for modal testing of a laminated cantilever blade. (1) Signal generator (2) Power amplifier (3) Electro dynamic exciter (4) Test beam (5) Accelerometer (6) Charge amplifier (7) Oscilloscope.

A cantilever, composite tapered beam with the same mentioned geometry and material properties was considered for finite element analysis using ANSYS software. Firstly, the crack location and depth similar to experimental procedure were considered. The first three flexural natural frequencies were extracted and compared with those obtained from experiments as shown in Table (2). Since the results are in good agreement, the finite element analysis can be used to generate many sets of input-output data for damage detection algorithm as it will be discussed later. Figure (4) shows the finite element modeling of the laminated composite tapered beam with transverse crack after meshing and applying boundary conditions.

In the present study, since the specimens are made of fiber glass/epoxy composite material, the finite element modeling of the cracked laminated composite beam is simulated with an eight node linear layered 3D shell element with six degrees of freedom at each node (specified as shell 99 element in ANSYS) as shown in Figure (5). Since each fabric layer corresponds to 2 different fiber orientation (fibers at 0^o and 90^o), two different layers were used to simulate each ply. Figure (6) shows the layer stacking using ANSYS. The finite element analysis using ANSYS software was used in modal analysis to obtain the natural frequencies. The cracked zone mesh has been properly refined and the convergent test was carried out for all the results.

Table (2): Results from experimental test and FEM (ANSYS).

Crack location (mm)	Crack depth (mm)	1st natural frequency (Hz)		2nd natural frequency (Hz)		3rd natural frequency (Hz)	
		ANSYS	Exp.	ANSYS	Exp.	ANSYS	Exp.
100	1	29.925	26.57	166.36	159.75	439.99	431.01
	3	29.764	26.43	166.34	159.74	439.6	430.62
	5	29.177	25.91	166.33	159.70	437.76	428.82
200	1	31.073	27.59	170.92	164.13	455.86	446.55
	3	31.001	27.53	170.4	163.63	454.93	445.64
	5	30.717	27.28	168.09	161.42	451.12	441.91
300	1	30.857	27.40	170.09	163.34	455.93	446.62
	3	30.85	27.40	169.29	162.57	454.72	445.44
	5	30.787	27.34	166.09	159.50	449.82	440.64
400	1	30.747	27.30	168.79	162.09	450.99	441.78
	3	30.733	27.29	168.63	161.93	449.36	440.18
	5	30.716	27.28	167.98	161.31	442.88	433.84
Healthy		31.986	28.41	173.66	166.77	459.64	450.26

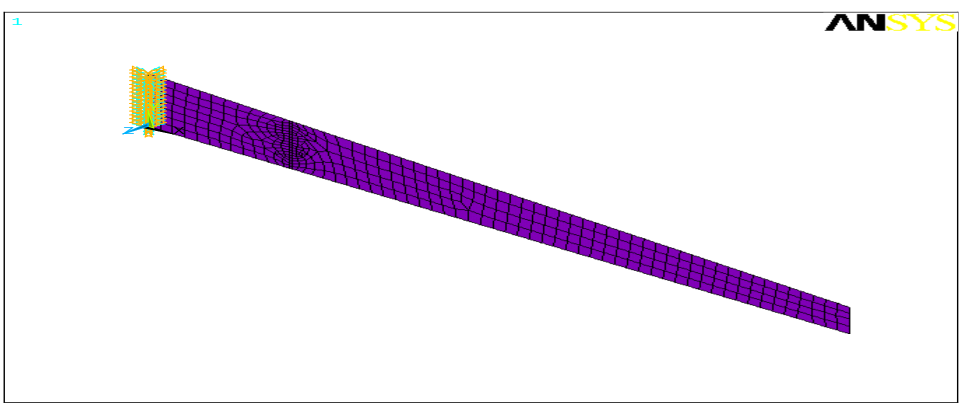

Figure (4): Finite element model of the cracked tapered beam.

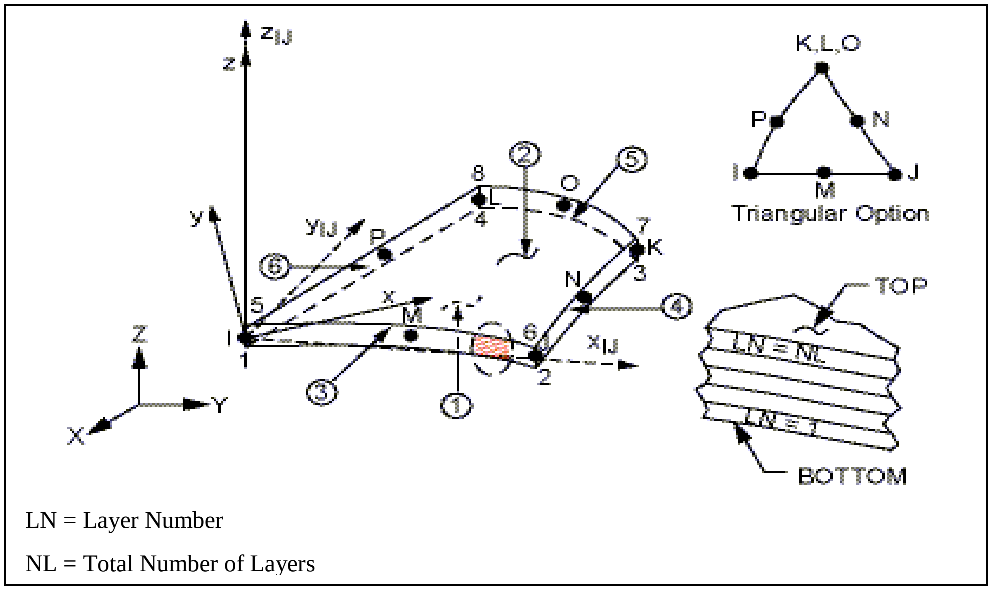

Figure (5): SHELL99 Element Geometry [9].

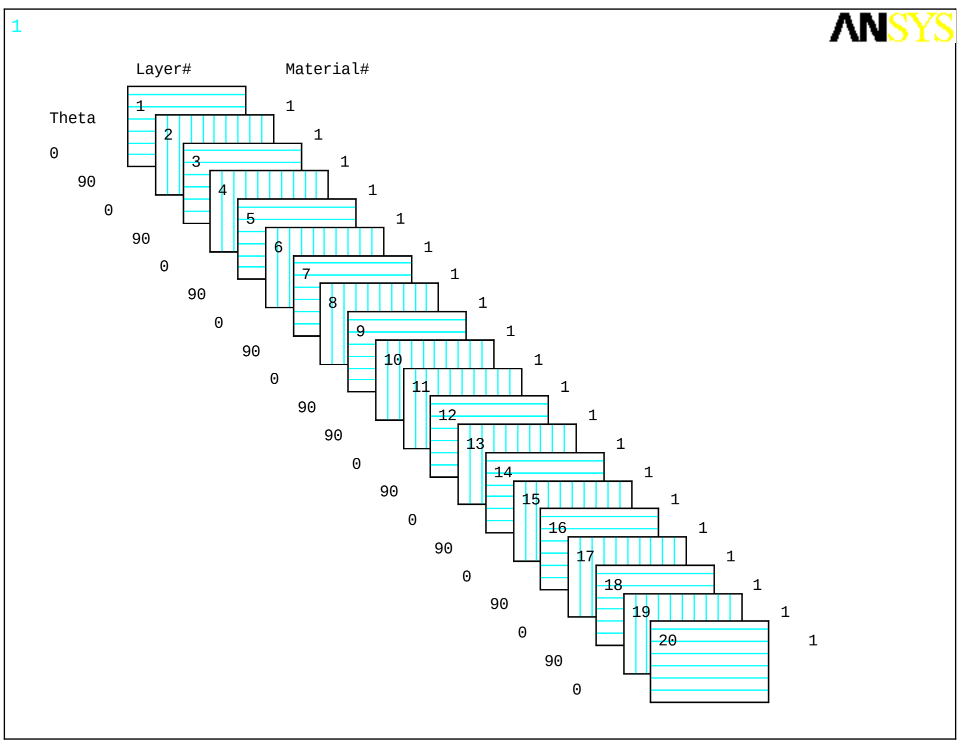

Figure (6): Layer stacking in ANSYS.

CRACK DETECTION USING ANN

Neural networks are powerful data analysis tools in modeling, Identification, diagnosis, and classification. Neural networks function is similar to the human brain. The first reason to this similarity is that a neural network acquires knowledge through learning and the second is that a neural network's knowledge is stored within inter-neuron connection strengths known as synapses. In order to use ANN for crack detection, it has to be trained for known crack specifications with their corresponding physical parameters [12].

In this work, the first three relative natural frequencies are employed to predict the crack location and crack depth of the composite tapered beam. It is noted that ANSYS is a powerful finite element software and capable of providing natural frequencies of the composite tapered beam with given crack location and depth. In order to develop and train a neural network, its input and output must be specified. Overall, 145 set of numerical input-output data for different crack specifications are obtained using ANSYS software. This set of data has been divided into training and testing data sets. Table (3) presents samples of the obtained numerical data. The first three relative natural frequencies of the composite tapered beam ($\omega^{i}_{c}/\omega^{i}_{o}$) are chosen as inputs, while the relative crack location (Lc/L) and crack depth (a/h) are chosen to be outputs. Thus three inputs –two outputs neural network would be a possible solution. A feed forward back propagation neural network has been adopted using Matlab environment. Each neural network consists of input, output and hidden layers. The input layer consists of just the inputs to the network, then it followed by hidden layers, which consists of any number of neurons. Finally, the networks outputs will be provided in the output layer. Figure (7) shows the proposed neural network's architecture which employs two hidden layers. The first hidden layer requires 20 neurons, while for the second one, a single neuron is sufficient. Each neuron performs a weighted summation of its input, which then passes a nonlinear activation function. Tan-sigmoid functions were used in all hidden layers and pure linear function in output layers. Levenberg-Marquardt algorithm is employed to train the network using the 'trainlm' function in Matlab [16].

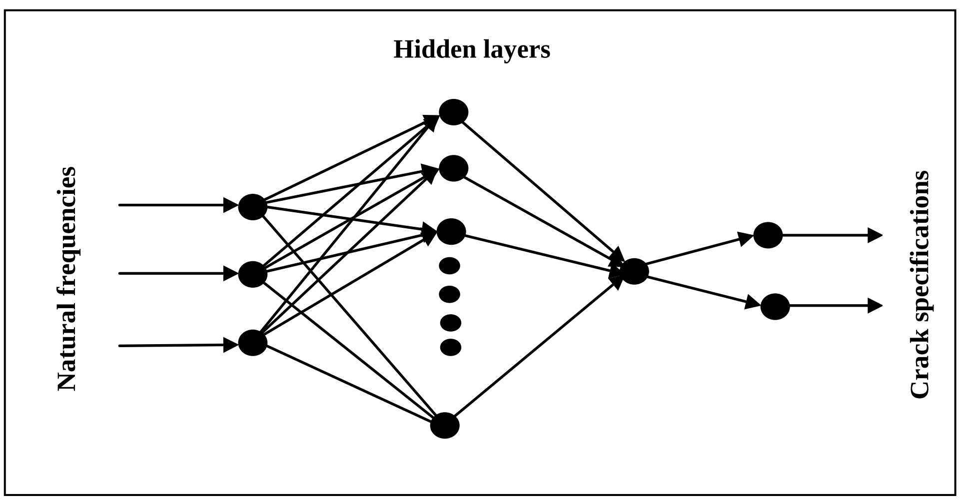

Figure (7): Schematic representation of the proposed ANN.

Table (3): Samples of actual data from FEM (ANSYS).

Crack No.	Crack location (mm)	Crack depth (mm)	1st natural frequency (Hz)	2nd natural frequency (Hz)	3rd natural frequency (Hz)
1	40	1	29.983	165.06	443.35
4	100	1	29.925	166.36	439.99
7	180	1	31.154	170.91	455.62
10	260	1	30.684	165.35	446.72
11	280	1	30.94	170.29	456.23
17	420	1	30.697	168.52	449.96
21	20	2	29.736	163.85	439.43
23	80	2	29.187	158.19	426.46
35	380	2	30.596	166.97	443.5
39	460	2	30.708	165.05	438.98
55	380	3	30.593	166.79	442.22
64	100	4	29.581	166.33	439.05
89	220	5	30.354	161.59	439.4
95	360	5	30.596	165.24	431.5
107	160	6	30.037	168.38	436.6
113	300	6	30.686	163.05	443.6
119	460	6	30.636	164.71	438.17
121	0	0	31.986	173.66	459.64

NUMERICAL RESULTS
NETWORK TRAINING

In the network training ,all weights in the network should be adjusted incrementally until the training data satisfy the desired (actual) data as well as possible; that is, until the network output approach the desired output with reasonable margins of error. Once the proper neural networks are constructed, 83% of the actual data set is used for the training procedure of the proposed networks. Figures (8) & (9) show the training results. It can be seen that the predicted value for the locations and depths obtained from the trained neural networks follow the exact pattern of the actual data set. Figures (10) & (11) show the error of crack location and crack depth for each crack case. From these graphs, it is concluded that the calculated error is small enough to say that the proposed networks predict the crack location and crack depth with high accuracy.

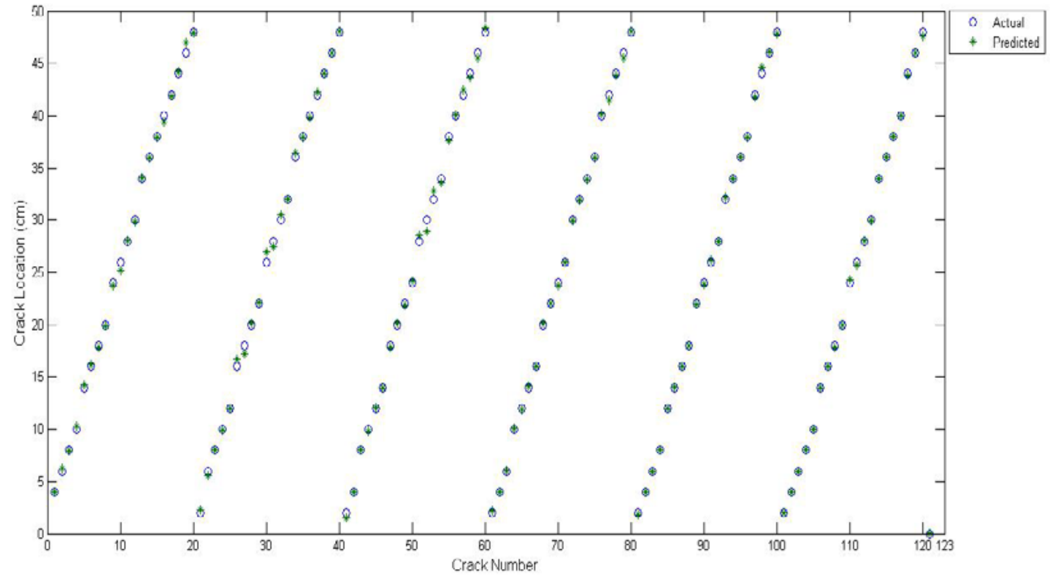

Figure (8): Trained network for crack location.

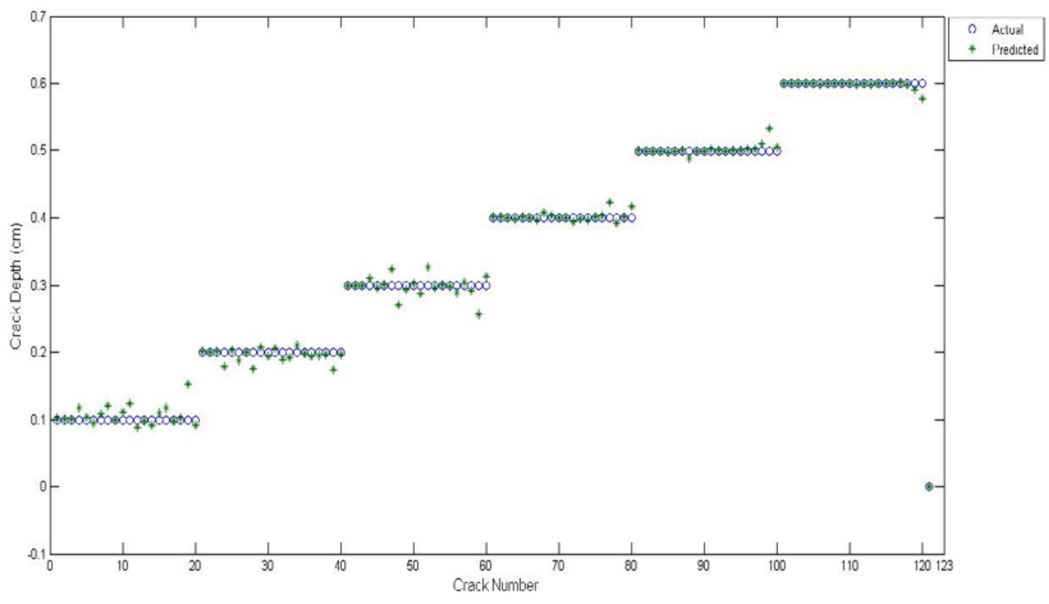

Figure (9): Trained network for crack depth.

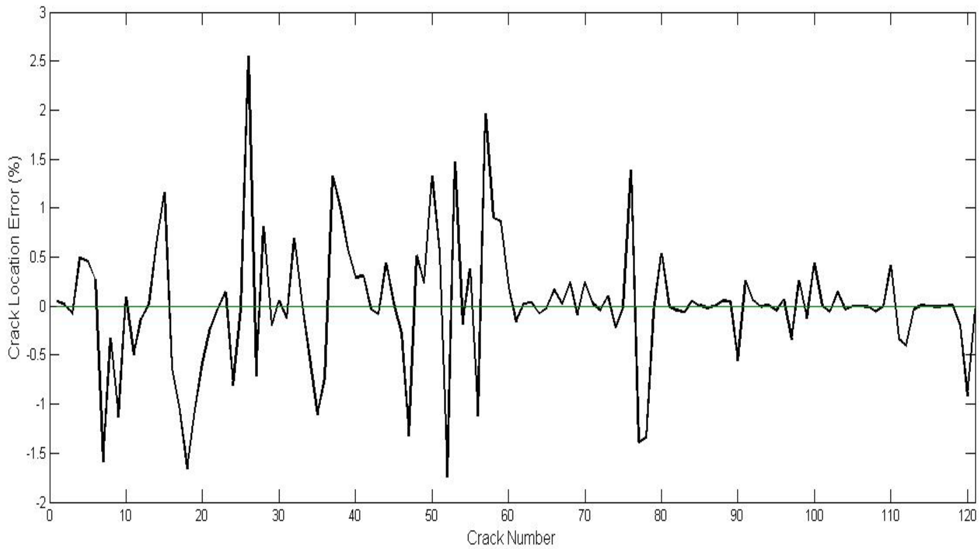

Figure (10): Crack location error diagram.

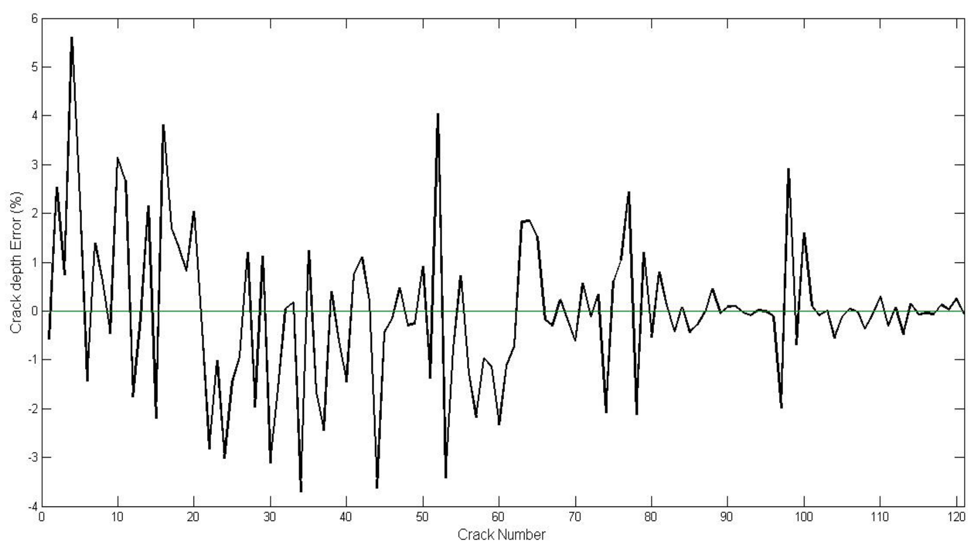

Figure (11): Crack depth error diagram.

NETWORK TESTING

Once the proposed neural networks are trained, some new data is required to test the performance of the accuracy of the trained ANN. An average of 17% of the actual untrained data set is used for testing the proposed neural network. The relative natural frequencies are fed to ANN as inputs. The outputs parameters of ANN are crack location and depth. Table (4) lists the actual and predicted crack location and depth for 24 different crack cases. The ANN can predict the crack location and depth for the test data with an accuracy of 97.5%, and 88.2% respectively.

Table (4): Comparison of actual and predicted crack depth and location.

Actual (ANSYS)		Predicted (ANN)	
Depth (mm)	Location (mm)	Depth (mm)	Location (mm)
1	20	1.2373	18.64
	120	1.2705	112.2
	220	1.3706	224.192
	320	1.3706	327.6578
2	40	1.8003	35.9588
	140	2.0307	137.5675
	240	2.0776	248.1962
	340	2.1334	355.7005
3	60	3.3348	56.8027
	160	3.3069	159.3674
	260	2.1943	243.4260
	360	3.6458	357.5213
4	80	3.9828	78.0312
	180	3.6287	180.5986
	280	3.8345	281.7089
	380	4.2872	377.2521
5	100	4.9978	99.5271
	200	3.6916	201.2595
	300	5.0188	291.1320
	400	5.6903	405.0169
6	120	5.9995	118.1577
	220	5.9976	220.4208
	320	6.1346	320.1868
	420	5.8045	419.0206

CONCLUSIONS

In this study the use of ANN to detect cracks in wind turbine blades has been investigated. The blade is approximated by a laminated composite tapered beam in this paper. The proposed detection approach is based on the structural dynamics of the wind turbine blade. The main conclusions that can be drawn from the results of the present investigation are:

- Due to the presence of crack, the wind turbine blade undergoes remarkable changes in natural frequencies.

- The artificial neural network technique considered here is used to predict the crack location and its depth by using the first three relative natural frequencies as inputs.
- The neural network predicted results are reasonably acceptable and in agreement with the FE numerical data which is in turn validated experimentally. Hence, it is concluded that neural networks are a valid tool to make an early detection of cracks in wind turbine blades.
- The successful detection of crack and its intensity in laminated composite blade demonstrates that the proposed technique in the present study can be used efficiently and effectively in crack identification of different laminated composite-type structures.

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