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Crack Identification in Blades

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ABSTRACT: In this paper a method for crack detection in blades is presented. In the suggested method, the process of crack identification is consists of four stages. In first stage, three natural frequencies of a blade for different locations and depths of cracks were calculated using Finite Element Method (FEM). The obtained results were verified with the results of experimental modal analysis. In second stage, two Multi Layer Feed Forward (MLFF) neural networks were created. In third stage, Genetic Algorithm (GA) was used to training the neural network. The inputs of neural networks were the first three natural frequencies and the outputs of first and second neural networks were corresponding locations and depths of cracks, respectively. In forth stage, some of natural frequencies of blade with different crack situations as inputs applied to trained neural networks. Finally obtained results showed that predicted cracks characteristics were in good agreements with actual data.
Keywords: crack detection, genetic algorithm, finite element method, experimental modal analysis, blade
Abbreviations: FEM: Finite Element Method, MLFF: Multi-Layer Feed Forward, GA: Genetic Algorithm

INTRUDUCTION

Crack is one of the common defects that if promotes, may cause catastrophic damages in engineering structures, so the detection of crack in structures came a very important issue. Many studies have been done on non-destructive estimation methods. The non-destructive methods used so far can be divided in four groups. The first group includes methods that determine if there is a specific fault in the structure or not (Cawley and Adams, 1979; Chance et al, 1994). The second group includes methods not only capable of identifying the fault but also locating it (Chance et al, 1994; Chen et al, 2003). The third group includes methods capable of specifying more information about the fault, like the depth (Chondros and Dimarogonas, 1980; Dimarogonas, 1996), and the fourth group contains methods that can even estimate the effect of the fault on the structure. In recently years between non-destructive methods of investigation of crack, researchers have showed more attention to vibration analysis and therefore lots of analytical, numerical and experimental works has been done in this field. Dimarogonas reviewed methods of investigating cracked structures in 1996(Douka et al, 2003). Crack causes a local flexibility in the structure which affects the dynamic behavior. For example it reduces the natural frequencies and changes the mode shapes. Analyzing these effects can be used for crack detection (Goudmunson, 1982). Dimarogonas et al. modeled a crack using local flexibility and calculated the equivalent stiffness utilizing fracture mechanics (He et al, 2001; Holland, 1975). Adams et al. developed an experimental technique to estimate the location and the depth of a crack based on the changes of the natural frequencies (Kao and Hung, 2003). In another investigation Dimarogonas presented methods which relate the depth of the crack to the changes of the natural frequencies when the crack location is known (Kaouk, 1994). These methods can be used to identify cracks in different structures. Gudmunson presented a method to predict the changes of the natural frequencies caused by faults such as cracks, notches, etc (Kim and Stubbs, 2003). Masoud et al (1998) investigated vibration characteristics of a fixed-fixed beam with a symmetric crack considering coupling effect of crack depth and axial load (Kim, 1995). Shen et al. presented a method based on minimizing the difference between the measured data the data obtained from an analytical data to identify cracks in an Euler-Bernoulli beam (Masoud et al, 1998). In this paper the parameter used to identify the fault is natural frequency. This is because of the fact that measuring natural frequency is cost effective (Ni et al, 2000), and can be done accurately in most structures (Goudmunson, 1982).

There are some articles about damage detection in blades. Srinivas et al. presented an optimization methodology for prediction of damage in rotating blades. Based on the available response amplitudes along various points in a harmonically excited blade with modal data, they defined a displacement residue in terms of unknown stiffness reduction coefficients. Then they predicted these coefficients by minimizing the norm of the residual vector using GA (Paipetis and Dimarogonas, 1986). In another study, Change and Chen presented a technique for blade damage detection based on spatial wavelet analysis (Pandey et al, 1991).

A new technique often used for damage identification in recent decades is neural network. Wu et al. used BEP neural network to detection of the location of the fault in a simple frame (Science, London). Ni et al. applied the probability ANN for detecting the damage in bridges (Shen and Taylor, 1991). Kao and Hung based on ANN, presented two stages method for identifying cracks. The first stage was identifying damaged and undamaged system situations and second stage was fault detection in structures. In this stage a trained ANN was used to produce free vibration response of the system and then the variations of amplitude and periods between the results were compared (Srinivas et al, 2008). Chen et al. applied the ANN for fault detection in engineering structures when excitation signal is not available (Stubbs and Global, 1990).

Optimization algorithms were used frequently for damage identification in recent years. Xiang et al. presented a crack identification method for detecting crack location and depth in a shaft. They construct the Rotating Rayleigh-Euler and Rayleigh-Timoshenko beam elements of B-spline wavelet on the interval (BSWI) to discretize slender shaft and stiffness disc, respectively. They modeled the cracked shaft by wavelet-based elements to gain precise frequencies. Then they used the first three measured frequencies in crack detection process and they identified the normalized crack location and depth by means of GA (Vandive JK. 1975). In another paper, He proposed a GA based method for shaft crack detection, which formulates the shaft crack detection as an optimization problem using FEM and utilizes genetic algorithms to search the solution (Wu X, et al, 1992).

This paper proposed a method for identification of crack in blades. Crack detection in this method is consists of four stages. First of all, the three natural frequencies of a blade for different locations and depths of cracks were calculated using FEM and validated with experimental modal analysis that was done in Sharif University of Technology. In next stage, two neural networks were created. Then, in third stage, GA was used for training the ANNs. First three natural frequencies, and corresponding locations and depths of cracks were used as inputs and outputs of neural networks, respectively. In the last stage, computed results achieved from ANN were compared with actual data.

Modal Analysis using FEM

The considered structure is a cantilever blade with geometrical, mechanical and material characteristic that have been tabulated in Table 1.

Table1. Geometrical, mechanical and material characteristics of the turbine blade

Blade length (mm)	Diameterofholenearther oot (mm)	Diameterofholefarfromr oot (mm)	Distancebetweentwoho les (mm)	Distancebetweenrootandit'snearhol enear (mm)	Yield Stress(MP a)
740	12	10	260	450	757
Poisso n Ratio	Density (Kg/m^3)	Elasticity Modulus (GPa)	Hardness HV10 (MPa)	Tensile Strength (MPa)	Relative tension (%)
0.3	7850	228	264	893	16

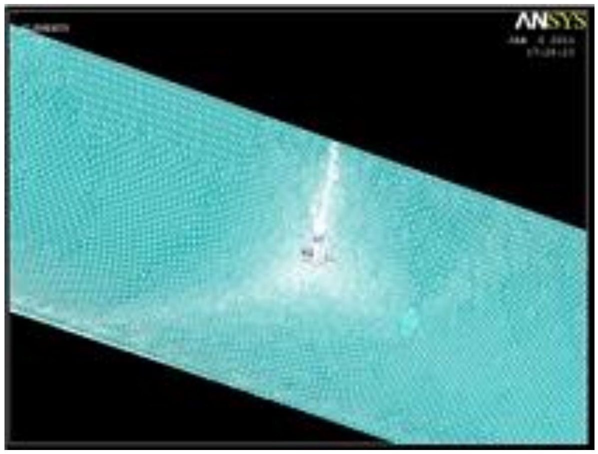

Figure1. Finite element discretization

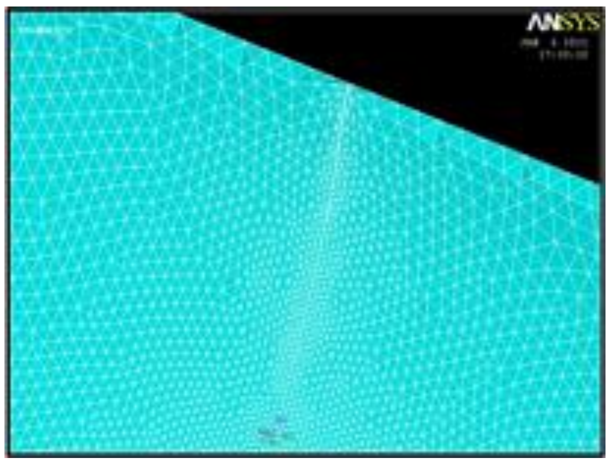

Figure2. Detailed of finite element discretization

Experimental Modal Analysis

For verification of FEM obtained results of present study, two natural frequencies of the blade were calculated for some variant conditions of crack and then they were compared with the corresponding results of experimental test (See Table 2). The experimental test was carried out in Condition Monitoring Laboratory of Sharif University of Technology. The cracked blade has been illustrated in Fig. 3. The crack location and depth in Table 2 showed in non-dimensional form. The non- dimensional location is the location of crack divided by lengths of blade. In addition, non-dimensional depth is depth of crack divided by depths of the blade. In experiment the length of blades was 74 cm, the depth of blade was 10.7 cm and the depth of cracks was 2.4 cm and 5.4 cm.

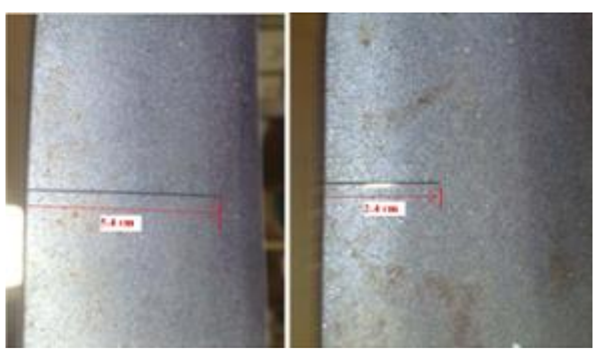

Figure3. The cracked blade

Table2. Comparison of Experimental and FEM results.

Condition		1	2
Non-dimensional Crack Depth		0.225	0.505
Non-dimensional Crack Location		0.46	0.46
Non-dimensional Natural Frequency, Experiment (HZ)	C_1	0.914	0.971
	C_2	0.936	0.992
Non-dimensional Natural Frequency, FEM (HZ)	C_1	0.926	0.987
	C_2	0.964	0.995
Error (%)	E_1	1.275	1.586
	E_2	2.901	0.312

In Table 2, natural frequency was presented respect to natural frequency of un-cracked blade. The equation (1) has been formulated this relation. Ei presents the percentage of error of FEM based on experimental data.

$$\%C_i = \frac{f_i^{cracked}}{f_i^{uncracked}} \times 100 \qquad (1)$$

Artificial Neural Network

Artificial neural networks offer an alternative way to tackle complex problems, and are applied in different applications like control, manufacturing, optimization, etc. The most popular type of neural network is Multi-Layer Feed Forward (MLFF). A schematic diagram of typical MLFF neural-network architecture is shown in Fig 4. The network usually consists of an input layer, some hidden layers and an output layer. Usually knowledge is stored as a set of connection weights. The process of modifying the connection weights, in some orderly fashion, using a suitable learning method is called training.

In this paper two distinct neural networks are employed for prediction of locations and depths of cracks. Networks consist of one input layer with 3 neurons, one hidden layer with 5 neurons and one output layer with one neuron. In each network, transfer functions for neurons of hidden and output layers are tensed and are defined as equation (2).

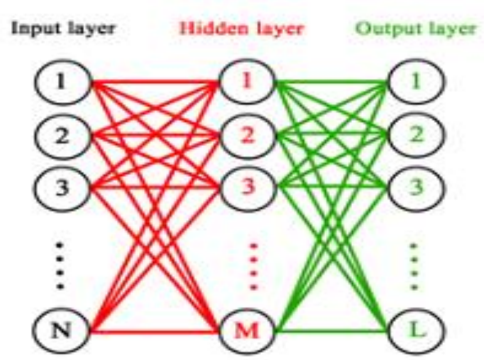

Figure4. Schematic diagram of multilayer feed forward neural network

$$f(x) = \frac{2}{(1 + \exp(-2n)) - 1} \qquad (2)$$

Genetic Algorithm

The GA is the most widely used optimization method in engineering problems. The GA was popularized by Holland (Wu X, et al, 1992) and has evolved into a global search method that simulates the evolution in complex physical and biological systems. A GA, at each iteration generates a population of points that approach the optimal solution by using stochastic and not deterministic operators. A GA starts by initializing a set of individuals that form the first population. Then the first population is submitted to genetic operators, resulting in the evolution of populations through generations (iteration cycles). In each generation, the GA evaluates the individuals according to objective function and selects the best individuals. The individuals that are evaluated as better, according to the objective function, have a higher possibility of participating in the recombination procedure. Mutation, which periodically changes parts of the individuals, is the main operator for protecting the algorithm from permanently losing genetic material through the evolution of generations. Crossover is used for the recombination of genetic exchange among individuals. Another operator is migration which is the movement of individuals among sub-populations of existing individuals, with the best individuals from one sub- population replacing the worst individuals in another sub-population. GAs proposes the best individual as the solution to the problem. A flowchart of a basic GA is shown in Fig. 5

Figure5. Flowchart of basic genetic algorithm

Crack Detection

In this section three different natural frequencies from four different crack conditions are applied to trained network as the input and the corresponding locations and depths are obtained as the outputs. Training the neural network has been done by using a procedure based on GA. In the procedure weights of ANN are the non-uniforms and root mean square of differences between outputs of ANN and target outputs is used as cost function. It is noteworthy that inputs and outputs of ANNs considered in normalized form. Since in the assumed network, there are 3, 5 and 1 neurons in input, hidden and output layers respectively, and since there are two biases in input and hidden layers, the number of non-uniforms of the optimization problem is 26. The GA that was used in this article consists of 4000 generations and 52 individuals.

RESULTS

The results of optimization problem for each of two ANNs are the optimized weights that are tabulated in Table 3. ANN1 and ANN2 are networks that are trained for prediction of location and depth of cracks, respectively.

Table3. Computed weights of ANNs

Weight	ANN1	ANN2	Weight	ANN1	ANN2
W11	3.174	3.221	W34	7.566	0.817
W12	7.981	6.731	W35	9.152	-3.095
W13	8.430	5.812	B11	1.342	-1.129
W14	7.385	-0.871	B12	4.909	2.806
W15	-0.348	-8.307	B13	8.158	2.071
W21	-0.704	0.794	B14	1.320	1.434
W22	8.251	7.373	B15	0.663	5.440
W23	0.207	9.373	V11	6.157	9.817
W24	-1.606	5.854	V21	0.489	4.120

In the above Table, Wij presents the weight of link that relates neuron number i from input layer to neuron number j from hidden layer. Also Vjk presents the weight of link that relates neuron number j from hidden layer to neuron number k from output layer. B1j present the weight of the link that relates bias of input layer to neuron number j of hidden layer and B2k present the weight of the link that relates bias of hidden layer to neuron number j of output layer. The predicted values of crack's locations and depths are compared with the actual values in Table 4. Also the diagrams of fitness value versus generation, best individual of each variables, best, worst and mean scores of each generation, and fitness of each individual at last generation were plotted using GA toolbox of Matlab Commercial Software that illustrated in Figs. 6 and 7, for detection of location and depth of crack, respectively.

Table4. Comparison of predicted and actual depths and locations of cracks

Number	Parameter	Predicted	Actual	Error (%)
1	Depth (mm)	4.345	4.4	1.24
	Location (mm)	32.732	32	2.29
2	Depth (mm)	3.632	3.6	0.89
	Location (mm)	35.181	36	2.27
3	Depth (mm)	2.3002		0.01
	Location (mm)	34.533		1.57

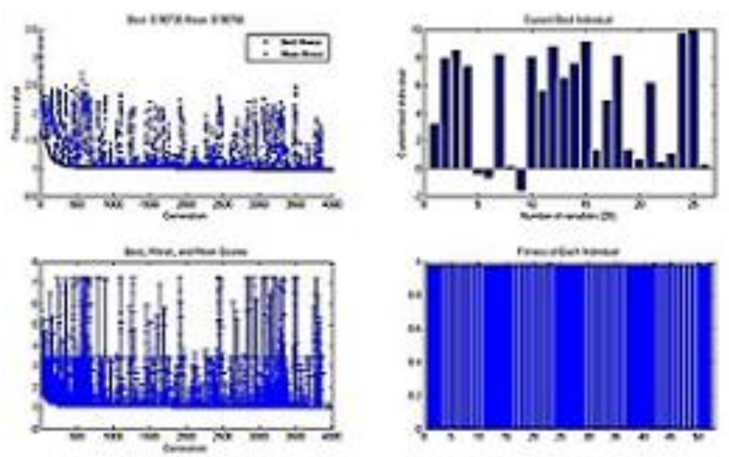

Figure6. Optimization procedure of runs of GA for detection of crack location using MATLAB

CONCLUSION

This paper, presented a procedure based on ANN and GA for identification of crack in blades. In the proposed procedure, first of all, three natural frequencies of a blade for different locations and depths of cracks were obtained using FEM and the results were verified with experimental analysis modal data. Then two MLFF neural networks were trained using GA algorithm for prediction of location and depth of cracks. Finally trained ANNs were used to predict the characteristics of some cracks on mentioned blade and the results were in good agreement with actual data, which the prediction errors were less than 2.3%.

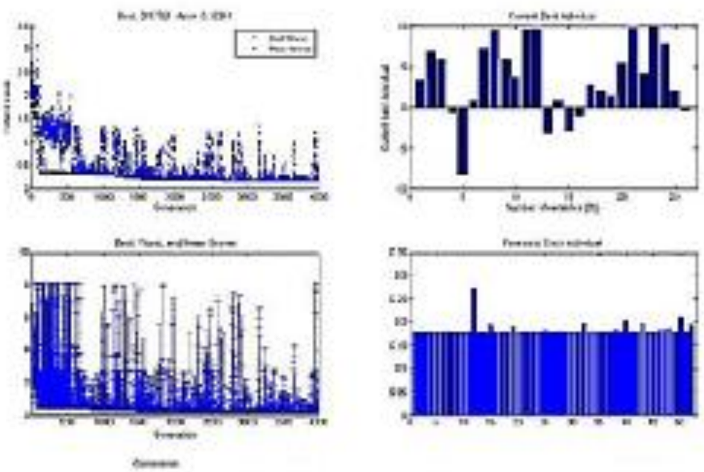

Figure7. Optimization procedure of runs of GA for detection of crack depth using MATLAB

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