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ANALYSIS OF SMART CRACK DETECTION METHODOLOGIES IN VARIOUS STRUCTURES

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ABSTRACT
The comprehensive review of numerous technical works in the area of crack identification in beam-like structures is described in this paper. Due to its simplicity, sensitivity analysis of experimentally observed frequencies has been widely employed in recent years as a fracture detection criterion. However, it is not simple to determine crack properties (such depth and position). The various methods are discussed in light of Crack's dynamic analysis. Artificial neural networks, fuzzy systems, hybrid neuro genetic algorithms, fuzzy logic neural networks, and artificial intelligence are the major methodologies.
Key words: Neural network, fuzzy logic, genetic algorithm, artificial intelligence, crack detection.

1. INTRODUCTION
Engineers and scientists have been developing numerous methods for spotting cracks in beam-like structures for the past few decades. Fuzzy logic, neural networks, artificial intelligence, etc. are commonly used in the most recent advances in crack detection in beam-like structures. Below are a few of the techniques used by researchers: Using six input parameters to the fuzzy member ship functions, Das et al. (2009) carried out analytical research on fuzzy inference system for fracture location and crack depth identification of a cracked cantilever beam construction. The first three mode forms of the cantilever beam and the % deviation of the first three natural frequencies make up the six input parameters. The fuzzy inference system's two output parameters are relative crack depth and relative crack location. For the purpose of testing the resilience of the created fuzzy inference system, an experimental setting has been created. The created fuzzy inference system is capable of accurately predicting the location and depth of the crack.
According to an approach put out by Taghi et al. (2008), damage to a broken structure was examined utilising genetic algorithm technology. An analytical model of a cracked cantilever beam was used to simulate the cracked-beam structure, and natural frequencies were calculated using numerical techniques. To keep track of any potential changes in the structure's inherent frequencies, a genetic algorithm is used. An optimization problem was developed to determine the position and depth of the fracture in the cantilever beam. (Bakhary et al., 2007) applied artificial neural network (ANN) for damage detection. In his investigation an ANN model was created by applying Rosenblueth’s point estimate method verified by Monte Carlo simulation, the statistics of the stiffness parameters were estimated. The probability of damage existence (PDE) was then calculated based on the probability density function of the existence of undamaged and damaged states. The developed approach was applied to detect simulated damage in a numerical steel portal frame model and also in a laboratory tested concrete slab. The effects of using different severity levels and noise levels on the damage detection results are discussed.
Damage assessment in structures from changes in static parameter using neural network is a

technique that Maity et al. (2004) introduced. In this study, a neural network was trained to detect the behaviour of both the undamaged and the structure in many conceivable damaged states. This trained network was capable of spotting any harm that already existed when it was exposed to the measured reaction. The idea was tested using a simple cantilever beam. Strain and displacement were two possible ways to look for injuries in the back.

Saridakis et al. (2008) used coupled response measurements to identify fractures in shafts using neural networks, evolutionary algorithms, and fuzzy logic. In this study, three measurements—position, depth, and relative angle—were used to characterise the dynamic behaviour of a shaft with two transverse fractures. Both fractures were assumed to be situated at random angles with respect to the shaft's longitudinal axis and some distance from the clamped end. Each fracture was modelled using a local compliance matrix with two degrees of freedom (bending in both the horizontal and vertical planes).. A technique for fracture damage identification was presented by Huijian Li et al. (2005). In order to predict the location and severity of crack damage in beam-like structures, he combined global (changes in natural frequencies) and local (strain mode shapes) vibration-based analysis data as input. He also used finite element analysis to determine the dynamic properties of both intact and damaged cantilever steel beams for the first three natural modes.

In order to identify macroscopic structural damage in a uniform strength beam, Panigrahi et al. (2009) first formulated an objective function for the genetic search optimization approach. They then introduced the residual force method. Here, two cases have been looked into. To show a unique example of a uniform strength beam, both width and depth are adjusted in the first case while maintaining the beam's uniform strength throughout.

The created model determines the position and severity of the damage in the beam using experimentally collected data as input. Here, experimental data are numerically simulated by including random noise in the vibration characteristics of finite element models of the structures.

The position and depth of a fracture in a structure may be determined utilising a hybrid neuro-genetic methodology, according to Suh et al. (2000). To understand the relationship between the input (the position and depth of a crack) and output (the structural eigen frequencies) of the structural system, feed-forward multi-layer neural networks trained by back-propagation are utilised. Genetic algorithm is utilised to determine the fracture location and depth by reducing the difference from the observed frequencies using this trained neural network.

The problem is originally described as an optimization problem, according to Huai Chou et al. (2001), and is then resolved using a genetic algorithm (GA). To determine changes in the defining characteristics of structural elements, such as Young's modulus and cross-sectional area, which are represented by the difference between measured and calculated displacements at a few degrees of freedom (DOFs), static measurements of displacements are utilised. GA is also used to calculate the displacements at unmeasured DOFs in order to avoid structural analyses in fitness evaluation. The proposed approach can identify the general area of the damage.

2. CRACK DETECTION USING ARTIFICIAL INTELLIGENCE TECHNIQUES

Numerous articles have investigated crack identification using both finite element approach and different classical methods. This study provides a brief overview of several artificial intelligence techniques that have been applied by researchers to the problem of fracture identification in damaged constructions.

2.1. NEURAL NETWORK METHOD FOR FAULT DIAGNOSIS OF CRACKED CANTILEVER BEAM

Six input parameters to the fuzzy member ship functions were used in an analytical study by Das et al. (2009) to determine the position and depth of a fracture in a damaged cantilever beam construction. The first three mode forms of the cantilever beam and the % deviation of the first three natural frequencies make up the six input parameters. The fuzzy inference system's two output parameters are relative crack depth and relative crack location. For the purpose of testing the resilience of the created fuzzy inference system, an experimental setting has been created. The crack's position and depth may be predicted by the created fuzzy inference system with high accuracies.

For the past forty years, there has been a lot of research done on the dynamics of structures having cracks. The existence of fracture causes variations in natural frequencies and mode shapes. The position and severity of the fracture substantially influence the variations of natural frequencies and mode shapes. Scientists are concentrating their efforts to identify the damage's location and degree.

Below are listed the investigations that were reported in this respect. Analytical findings are utilised to connect the recorded vibration modes to the crack location and depth in a rectangular cross-section cantilever beam with a transverse surface crack that extends evenly over the width of the beam (Rizos et al., 1990). The fracture position and depth may be determined with sufficient precision using the observed amplitudes at two places of the structure vibrating at one of its natural modes, the corresponding vibration frequency, and an analytical solution of the dynamic response. Free and forced response measurements may be used to determine the fracture localisation and size technique in a beam (Karthikeyan et al., 2007). In order to manage the ill-conditioned system equations that arise in the experimental research, a method utilising singular value decomposition is created.the changed structure's observed natural frequencies. An comprehensive investigation on the identification of structural fracture damage has been conducted (Akgun et al., 1983). For the purpose of identifying fracture damage in straightforward structures, the idea of a "fracture hinge" is created analytically and applied to a fractured section. It has been demonstrated through experimentation that a spring-loaded hinge can accurately simulate the structural impact of a fractured portion.Due to its capacity to match patterns, artificial neural networks (ANN) can be a useful alternative tool for tackling inverse issues (Sahoo et al., 2007). The ANN findings show the robustness of the suggested damage assessment approach and are extremely positive. Two separate artificial neural network techniques—feed forward network with back propagation algorithm and binary adaptive resonance network—are used to construct the defect detection model (ART1). For a total of seven different sorts of defects in the centrifugal pumping system, the performance of the designed back propagation and ART1 model is evaluated. Analytical calculations are made to determine the modal frequency characteristics for the flexural vibration of a cantilever beam with a transverse surface fracture for different crack locations and depths.An artificial neural network is trained to recognise the position and depth of the fracture using the calculated modal frequencies. A non-destructive method for monitoring the health of structures may be employed using this modular neural network design. For the purpose of predicting the location and degree of damage in beam-like structures, a damage detection method has been created utilising a mix of global (changes in natural frequencies) and local (curvature mode shapes) vibration analysis data as input (Sahin et al., 2003). The trained feed-forward back propagation ANNs are tested for damage quantification and localisation using the data from the experimental damage case. An innovative strategy for predicting the position and strength of cracks has been put forth by Das et al. (2009).

2.2. GENETIC ALGORITHM METHOD FOR FAULT DETECTION IN BEAM- LIKE STRUCTURES

According to an approach put out by Taghi et al. (2008), damage to a broken structure was examined utilising genetic algorithm technology. An analytical model of a cracked cantilever beam was used to simulate the cracked-beam structure, and natural frequencies were calculated using numerical techniques. To keep track of any potential changes in the structure's inherent frequencies, a genetic algorithm is used. An optimization problem was developed to identify the position and depth of the fracture in the cantilever beam.

Cracks are the primary reason for structural failure in beams, which are ubiquitous structures used to transport and transfer heavy loads in machinery and civil constructions. Early fracture identification is crucial since sudden failure under high load operation might have severe consequences. In order to explore the important changes in the structural characteristics and forecast an unexpected failure, non-destructive inspection techniques are typically applied. Using online damage assessment tools, which measure vibration parameters to reveal the overall health of the structures, damage may be identified, quantified, and localised. A fracture often results in a decrease in the structure's rigidity and an increase in its damping.Reduced natural frequencies and a divergence in the mode shape are results of these changes in physical attributes. As a result, by monitoring changes in the vibration characteristics, a crack's position and depth may be predicted. Since frequencies can be measured more readily than mode shapes and are less severely influenced by experimental mistakes, changes in the natural frequencies are employed more frequently than deviation of mode forms (Morassi et al., 2001). Taghi et al. (2008) suggested a GA-based method for estimating fracture size. A description of the position and depth in an aluminium beam is given, along with some recommendations for choosing the GA parameters. Hamilton's principle is applied to create the equations for the motion of the broken beam. The damage effect is described as a torsional spring (Rizos et al., 1990). The natural frequencies of the beam are then obtained by solving the eigenvalue problem. Finite element analysis offers a different approach for determining the natural frequencies of a fractured beam (Rizos et al., 1990), however it is less precise than the continuous model employed in this article. The identification of the location and depth of a crack in a cantilever beam is formulated as an optimization problem, and binary and continuous genetic algorithms (BGA, CGA) are used to find the best location and depth by minimising the cost function, which is based on the difference between measured and calculated frequencies. When compared to conventional GAs, a GA with a small population size and high mutation rate is utilised, which results in a considerable exploration of the search space with a minimal amount of cost function evaluations. In order to maximise the likelihood of finding the global minimum as opposed to a local one, we repeat the GA using five alternative beginning points (variables) and select the best solution. the right way around.

The variables in BGA are represented by a total of 21 bits, while in CGA there is no need to convert the variable values. The obtained results demonstrate higher accuracy of the CGA over the BGA. The various process used in GA as follows:

1. Selecting the variables and cost function
2. The gene size
3. Initial population
3. Cost evaluation
4. Selection
5. Reproduction

6. Mutation
7. Re-evaluating the costs and iterating the algorithm.
8. Stopping criteria (Based upon fitness function)

2.3. ARTIFICIAL NEURAL NETWORK METHOD FOR FAULT DETECTION USING WITH CONSIDERATION OF UNCERTAINTIES

Artificial Neural Network was used by Bakhary et al. (2007) for damage identification. Rosenblueth's point estimate approach was used in his inquiry to build an ANN model, and the stiffness parameter statistics were obtained using Monte Carlo simulation. The probability density function of the presence of the undamaged and damaged states was then used to compute the probability of damage existence (PDE). The devised method was used to spot simulated damage in both a concrete slab that had been tested in a lab and a numerical steel portal frame model. On the outcomes of damage detection, the impacts of utilising various severity and noise levels are explored.

Many researchers have used artificial neural networks (ANN) to determine the location and degree of damage from multiple input and output variables since they are an effective tool for pattern recognition. In a 3-storey frame, Wu et al. (1992) investigated the application of an ANN to identify member damage. In their work diagnosing deterioration in a 21-bar bridge truss, Pandey et al. (1995) gave a more thorough discussion of ANN design.

A counter- propagation neural network was used by Zhao et al. (1998) to detect damage and assist movement in a continuous beam. A method for assessing steel structural damage based on ANN was created by Zapico et al. in 2001. The majority of investigations came to the conclusion that ANNs are capable of correctly identifying damage, particularly when the structural damage and the changes in vibration characteristics are accurately and numerically modelled. In actuality, though, FE model parameter uncertainties and modelling mistakes are unavoidable. The vibration parameters obtained from such a FE model may not precisely represent the actual phenomenon because of modelling error caused by inaccurate physical parameters, imperfect boundary conditions, finite element discretization, and nonlinear structural features.

Since the efficiency of an ANN prediction relies on the accuracy of both components, the existence of these uncertainties may result in false and inaccurate ANN predictions. Therefore, the impact of uncertainties on the reliability of ANN models for structural damage detection needs to be analysed. The objective of this paper is to study the influence of uncertainty on damage identify- cation using a combination of frequency and mode shape as the input variables. To consider the uncertainties in the FE modelling and the measurement data, an approach introduced by Papadopoulos et al. (1998) is applied. Using this method, the probability of damage existence (PDE) can be estimated by comparing the probability distribution of the undamaged and damaged models. To consider the effect of FE modelling error, a statistical ANN model is trained with vibration data generated from the FE model, but smeared with random variations. To include the effect of noise in the measurement data, the testing data used as input to the statistical ANN model for damage identification are also smeared with random noises.

The probability moments of the undamaged and damaged states of the structural parameters are esti- mated using the point estimation method and verified by Monte Carlo simulation. The Monte Carlo simulation data is also used to determine the type of probability distribution function of the structural parameters of both the undamaged and damaged states. The PDEs are determined from the probability distribution for each structural member.

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2.4. DAMAGE ASSESSMENT IN STRUCTURE FROM CHANGES IN STATIC PARAMETER USING NEURAL NETWORKS

A technique termed damage assessment in structures from changes in static parameter using neural network was introduced by Maity et al. in 2004. In this study, a neural network was trained to detect the behaviour of both the undamaged and the structure in many conceivable damaged states. This trained network was capable of spotting any harm that already existed when it was exposed to the measured reaction. The concept was tested on a simple cantilever beam. A back propagation neural network employed strain and displacement as potential possibilities for identifying damage, and it was found that strain performed better than displacement in doing so.

The objective of the above method is to locate and assess the damage occurring at any position in a cantilever beam by back-propagation neural network considering displacement and strain as input parameter to the network. The approach here consists of three sub- processes. Firstly, by varying the model parameters of the structure, their corresponding response to the system is calculated through the finite element method. Secondly, a neural network is iteratively trained using a number of training patterns. Here, structural responses are given as input to the neural network. Finally some structural responses measured are given to the well-trained network, which immediately outputs the appropriate value of parameters for untrained patterns. The model parameter taken here is the EI value of the structural member and the structural responses are displacement and strain for a comparison of the performance of the damage assessment algorithm.

2.5. VIBRATION BASED DAMAGE DETECTION IN A UNIFORM STRENGTH BEAM USING GENETIC ALGORITHM

Panigrahi et al. (2009) firstly formulated an objective function for the genetic search optimization procedure along with the residual force method presented for the identification of macroscopic structural damage in an uniform strength beam. Two cases have been investi- gated here. In the first case the width is varied keeping the strength of beam uniform throughout and in the second case both width and depth are varied to represent a special case of uniform strength beam. The developed model requires experimentally determined data as input and detects the location and extent of the damage in the beam. Here, experimental data are simulated numerically by using finite element models of structures with inclusion of random noise on the vibration characteristics.

In this paper the authors used roulette wheel selection criteria for damage identification of uniform simple supported beam as well as for cantilever beam. Fault classification has been done for cylindrical shells with auto associative neural network along with GA in reference (Marawala et al., 2006). As compared with the traditional optimization and search algorithms, GA search from a population of points in the region of the whole solution space, rather than a single point, and can obtain the global optimum. Other advantages of using GA are that it is a self-start method with no special requirement on the initial value of unknown parameters, other than defining a search range, and also it does not need information such as gradients or derivatives of the function to be minimised.

Moreover, GA has the advantage of easy computer implementation. These properties make GA successful and powerful in the field of structural optimization (Rajasekaran et al., 2003). Genetic algorithm (GA) has been established which may be used intelligently to identify and quantify the damage in a uniform strength beam. Rao et al. (2004a, b) have used this procedure for uniform cantilever beam, truss structures and portal frames. Panigrahi et al. (2007) addressed the problem of damage identification in a cantilever beam with uniform thickness only by changing the selection methods in GA. Here GA along with residual force vector method has been used for damage identification of a uniform strength beam with variation of depth along its length and another case with both width and depth varying. In the present paper, first the concept of residual force vector is intro- duced to specify an objective function for an optimization procedure, which is then solved by using G.A. The aim is to formulate an objective function in terms of parameters related to the physical properties and state of the structure. The objective function must be formulated in such a way that the minimum or null value is obtained when evaluated with true parameters of the structure. Here the parameters used are the damage factors which are nothing but the reduction in stiffness factor. GA is employed to determine the values of these parameters by following an iteration process. In this study a method known as steady-state selection is selected for reproduction purpose in GA which requires less number of iterations (Michalewicz, 1994).

The main idea of the selection is that bigger part of the chromosome should survive to next generation. When the objective function is optimized, values of the parameters indicate the state of the structure. Two cases have been investigated in this study. In the first case, a uniform strength beam with inclusion of slope function in width has been discussed. The second case demonstrates this method with inclusion of slope functions for both the depth and width of the beam. For simulating the experimental measure-ment, the vibration characteristics viz. natural frequencies and the mode shapes were perturbed randomly. A computer program using MatLab is employed to find out the location and extent of the damage.

2.6. CRACK IDENTIFICATION BY THE METHOD OF HYBRID NEURO- GENETIC TECHNIQUE

The position and depth of a fracture in a structure may be determined utilising a hybrid neuro-genetic methodology, according to Suh et al. (2000). To understand the relationship between the input (the position and depth of a crack) and output (the structural eigen frequencies) of the structural system, feed-forward multi-layer neural networks trained by back-propagation are utilised. Genetic algorithm is utilised to determine the fracture location and depth by reducing the difference from the observed frequencies using this trained neural network. Because they can handle the study of structural damage without the need for extensive computing, neural networks have been used in damage detection for a number of years. Neural networks are now anticipated to be required for heavy computing.

Recently, neural networks are expected to be a potential approach to detect the damage of the structure (Furukawa et al., 1995). In these researches, both the modal frequencies and the modal shapes are needed for the training of neural network to detect the structural damage, since the frequency information alone is not sufficient to train the neural network for the inverse problem of the crack identification.

To identify the locationnand depth of a crack in a structure with only frequency information, a method is presented in this paper which uses hybrid neuro-genetic technique.

Feed-forward multi-layer neural networks trained by back-propagation are used to learn the input (the location and depth of a crack)-output (the structural eigen frequencies) relation of the structural system. With this trained neural network, genetic algorithm is used to identify the crack location and depth minimizing the difference from the measured frequencies. This approach needs only the modal frequencies for use of hybrid neuro-genetic techniques.

2.7. FUNDAMENTAL STRUCTURE OF THE GENETIC ALGORITHM

There is preparation phase and application phase. In the preparation phase, firstly, the learning

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data of various sets of crack parameters and the corresponding response of the structure, which is the eigen frequency in this study, are prepared by the computational structure analysis. Figure 1 shows the various processes involved in genetic algorithm. In this Various fuzzy inference and fuzzy-genetic algorithm methods followed for crack identification are outlined.

In a composite matrix cracking model, Pawar et al. (2007) employed a genetic fuzzy system to pinpoint the position of the crack depth. He noted that the success rate of the genetic fuzzy system in the presence of noise depends on crack density and that it combines the fuzzy logic's qualities of uncertainty with the genetic algorithm's capacity for learning. Even in the presence of noisy data, he has discovered that the genetic fuzzy system has remarkable damage detection capabilities.

A fuzzy inference method for crack location and fracture depth identification of a cracked cantilever beam has been suggested by Das et al. (2008). It uses the percentage deviation of the first three natural frequencies and the first three mode shapes by the fuzzy member ship functions. The fuzzy inference system's two output parameters are relative crack depth and relative crack location. The fuzzy rules are derived from the vibration signatures, and an experimental setup has been established to test the resilience of the created fuzzy inference system.

Wada et al. (1991) have proposed a fuzzy control method with triangular type membership functions using an image processing unit to control the level of granules inside a hopper. He has stated that the image processing unit can be used as a detecting element and with the use of fuzzy reasoning methods good process responses are

t=0;

Initialize P(t); do

Crossover P(t); Mutate P(t); Evaluate P(t); Select P(t); t=t+1;

While terminal condition is not satisfied obtained.

In their study on the use of fuzzy logic to medical diagnosis, Fox et al. (1977) presented a wide variety of concerns on the contribution of information-processing techniques to the advancement of medical computers.

An intelligent method based on fuzzy-genetic algorithm (FGA) has been developed by Lo et al. (2007) for automatically identifying HVAC system defects. The suggested automated fault detection system (AFD) uses a fuzzy system to continually monitor the condition of the HVAC system, and the capacity of genetic algorithms to optimise permits the creation of the best possible fuzzy rules. The suggested automated fault detection (AFD) system for the single zone air handler system is validated by simulation studies, as indicated.

The AI approach was used by Parhi et al. (2008) to detect a cracked beam flaw. In this study, a fuzzy controller was employed to determine the relative fracture position and depth of the cracked beam. The first three relative mode shape differences and the percentage deviation of the first three relative natural frequencies serve as the fuzzy controller's input parameters. Natural frequencies, mode shapes, fracture depths, and crack locations are used to put up the fuzzy rules. In this study, the output of a fuzzy controller has been experimentally confirmed.

Fuzzy linear programming was used by Zimmermann et al. (1978) to solve the linear vector maximum problem. Fuzzy linear programming is used to find the solutions. These have been discovered to be more effective vector maximum issue solutions than the various models put forth.

3. DISCUSSION

The neural network technique has been discussed for detection of the relative crack location and relative crack depth.

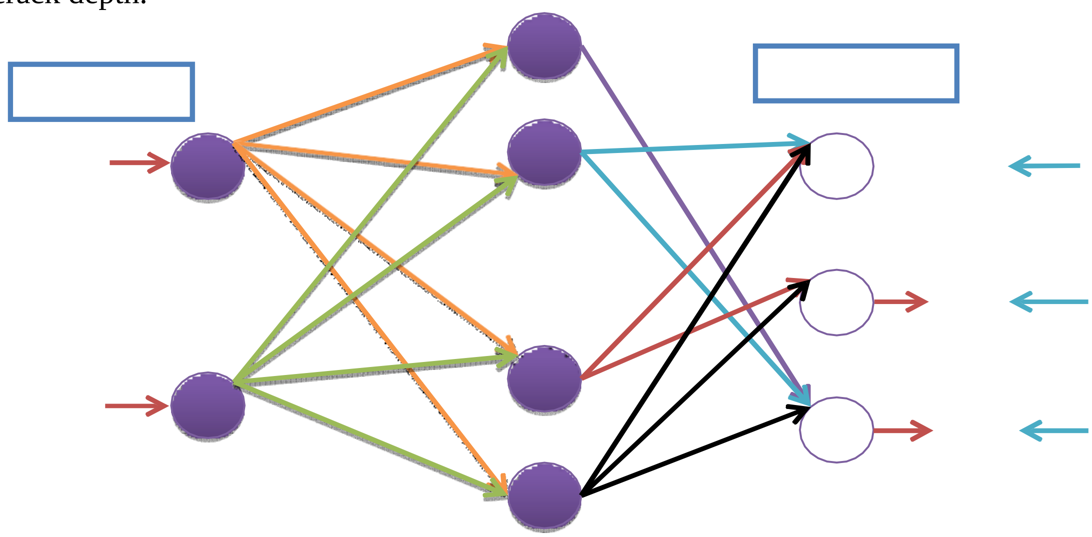

Figure 2. Three layer Neural Network utilized in this study.

The neural network has got six input parameters and two output parameters. The structure of the neural network has been shown in Figure 2. The inputs to the neural network are as follows;
Relative first natural frequency = “fnf”;
relative second natural frequency = “snf”;
relative third natural frequency= “tnf”;
relative first mode shape difference = “fmd”;
relative second mode shape difference = “smd”
and relative third mode shape difference = “tmd”.
The outputs from the neural network are as follows; Relative crack location = “rcl” and Relative crack depth = “rcd”.

The back propagation neural network has got ten layers (that is, input layer, output layer and eight hidden layers). The neurons associated with the input and output layers are six and two respectively. The neurons associated in the eight hidden layers are twelve, thirty-six, fifty, one hundred fifty, three hundred, one hundred fifty, fifty and eight respectively. The input layer neurons represent relative deviation of first three natural frequencies and first three relative mode shape difference. The output layer neurons represent relative crack location and relative crack depth. A genetic algorithm approach for detecting cracks in beam-like structures has been analyzed. The search process proposed in this method utilizes binary and continuous genetic algorithms to find the crack location and depth whose natural frequencies have maximum similarity with the input natural frequencies. Also a new cost function based on natural frequencies was presented. Some guidelines for selecting GA parameters are provided. In comparison with traditional GAs, we use a GA with small population size combined with a large mutation rate, so the great exploration of the search space with small number of cost function evaluation is achieved. A statistical ANN method gives a good value in that accounts for the inevitable FE modeling error and measurement noise for structural condition identification. Rosenblueth’s point estimation method is used to derive the statistical ANN model and to identify the structural condition. Both the modeling error and measurement noise are assumed to have normal distribution and zero means. The accuracy of the statistical approach was proved using Monte Carlo simulation. Using this method, the probability of damage existence can be estimated. The numerical and experimental results demonstrated that, compared with the normal ANN approach, the statistical ANN approach gives more reliable identification of structural damage. Condition monitoring tools like expert system, acoustic emission, shock pulse method and extended neuro-fuzzy schemes are proposed for a real time machinery condi- tion monitoring. The uses of various Artificial Intelligence (AI) methods for fault detection are discussed briefly. The genetic fuzzy system combines the uncertain characteristics of fuzzy logic with the learning ability of genetic algorithm which shows an excellent capability for damage detection even in the presence of noise data. The fuzzy technique can be used for fault detection by feeding the percentage deviation of first three natural frequencies and relative mode shapes as input parameters to the fuzzy controller. Fuzzy control method with triangular type membership functions and image processing unit can be used in a manufacturing environment for optimize the input and output parameters. Probabilistic neural network, artificial neural network, fuzzy proportional integral (PI), genetic algorithm, neuro fuzzy, evolution based fuzzy neural diagnostic can be used for fault diagnosis in mechanical and electrical machines. A computer code is developed in which structural response due to damage is carried out. The response data are fed into the network to determined the damage. It is observed that neural networks can successfully identify and calculate the amount of damage for both single and multiple element damage cases. The main advantage of a neural network is that response measurement is required only at a limited number of points.

4. CONCLUSION

In this study, many strategies and techniques for fracture detection in the context of dynamic vibration of cracked structures have been comprehensively examined. Their applications for damage detection have also been briefly discussed. .Based on the current analysis, it has been found that different Artificial Intelligence (AI) methods, such as genetic algorithm, neural network, and fuzzy inference technique, are successfully used for calculation of damage severity, which is the location and depth of the crack of cracked structures, in addition to conventional methods such as classical, finite element method.

- The finite element method has been used to find out the natural frequencies, and mode shapes of the cracked beam which are being used to locate the crack location and size.
- The fuzzy controller has been used to find out the relative crack depth and relative crack location of the cracked beam.
- The genetic controller has been used to find out the relative crack depth and relative crack location of the cantilever beam.
- Some of the researchers have also applied neural network for crack identification in damaged vibrating structures like artificial neural network, hybrid neuro genetic technique.
- In some of the analysis the fuzzy technique, neural network and genetic algorithm are applied in combination to detect depth and location of the damage.

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