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Investigation of Crack Properties Using Artificial Neural Network Approach

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Abstract

This paper displays the investigation of the crack properties of a whirling shaft using anexperimental and an artificial neural network approach. It is found thatthecracks in the mechanical systems leads to failure of system. Prediction of cracks plays an important role in today's world. Artificial neural networks (ANN) based modelling, a field of artificial intelligence, is used in this paper as an alternative method for crack detection. The growth of ANN has opened the door to new possibilities in the field of complicated system problems. The fundamental advantage of using ANN in network modelling is that networks can be constructed directly from experimental data by exploiting their self-organising capabilities.The dynamic properties of a shaft such as mode shape, natural frequency and critical speed change in the presence of cracks. The investigation is done on the whirling of shafts to obtain the critical speeds. The shaft is modelled in CATIA (a 3D modelling software) with crack depths 3, 5 and 7 mm and are analysed usingANSYS 16.0 software to obtain the natural frequencies of the shaft with crack spacing of 75, 150, 220 and 300 mm. The total length of the shaft considered here is 650 mm. These experimental values wereused as input to the artificial neural network to predict the crack position and severity. The crack depth and crack locations are predicted with an accuracy of 99.98%.

Keywords: Artificial Neural Network, Whirling of the shaft, Mode shapes, Critical speed, Modal Analysis, Natural Frequency.

Abbrevations

CAD	Computer Aided Designing
3D	Three Dimensional
ANSYS	Analysis of Systems
ANN	Artificial Neural Network
FEA	Finite Element Analysis
RPM	Revolutions Per Minute
NDT	Non – Destructive Testing
HZ	Hertz

1. Introduction

The condition of the rotor system of a rotating machine has a direct effect on the normal operation of the equipment. However, because rotor systems are often operated in high temperature and high-pressure environments, stress concentrations occur on the rotating shaft, and fatigue cracks may gradually form over time due to the long-term effects of complex alternating loads at high speeds. After reaching a certain depth, the rate of crack propagation increases dramatically and the rotating shaft is likely to break very quickly, leading to mechanical equipment failure, resulting in huge economic losses and even potentially catastrophic accidents. Structural monitoring of the condition of a rotor system can detect the breakage in time and prevent the loss of life and property.

1.1 Background

Failure of mechanical systems can have a variety of causes, including excessive load or stress, poor design, or a flaw in the materials used. [1] Damage to structures over time reduces their safety and, in some cases, even leads to structural failure [2]. One of the main causes of structural collapse is cracks in structures. In recent years, NDT methods, vibration-based methods and other mathematical models have been used to study the diagnosis of a single fracture.

1.2 Motivation

The discovery of cracks in spinning machine shafts has attracted the interest of a number of scientists from all over the world. A number of methods have been developed in recent years, with vibration-based options proving to be the most effective. One way of detecting shaft alignment problems is vibration analysis, which involves monitoring 1, 2 or 3 axes of motion [1]. Crack detection is usually done by monitoring the 1X, 2X and 3X vibration components [2]. For rotating machines, advanced approaches that can detect cracks early are desirable. Damage to a machine's shaft can lead to lost production or require the machine to be shut down completely. This could result in financial damage as well as loss of life. This can be avoided by monitoring the severity of cracks in the shaft. This motivates the current research work to identify the severity and location of the damage inside the shaft. An artificial neural network is a novel method to predict the location of damage and its severity.

1.3 Objective of the Research

These following are the objectives of the paper.

1. Find damage location and its severity in a shaft.
2. Design of shaft with cracks &Carry out FEA analysis to obtain mode shape and natural frequencies of a shaft with crack.
3. Experimental verification of critical speed and natural frequencies.

1.4 Literature Review

J. Prawin et al. found that there is little change in the dynamic properties of the shaft due to a breathing crack compared to an open crack. Zero strain energy method was used to identify the damage location. Harmonic excitation used to identify the damage site. The crack in the structure was located using a single sensor. The proposed method was numerically simulated to obtain results. The numerical results were validated using experimental results [1]. Shuihua Zeng et al. observed the natural frequency response of a cylindrical container with liquid inside. The wave propagation method was used to study the natural frequency behaviour of a cylindrical container. A local flexibility matrix was constructed to determine the crack stress and displacement. Crack detection using vibration energy flux. Comparison of the vibration response of the cylindrical shell was carried out before and after cracking. It was found that the crack position has a greater effect on the natural frequency of the structure [2].X. Zhou et al. studied the mode shape and natural frequencies of a drill riser. The mode shape and natural frequencies were extracted using a calculation code. Numerical method to verify the natural frequencies from the computational code. The modal curvature method was used to identify cracks in the mid and end sections of the drill riser. The natural frequencies were affected by the presence of cracks. It was found that open cracks were more easily identified using the modal curvature method and natural frequencies [3].J.T. Ravi et al. used a one-dimensional neural network to detect cracks in concrete bridges. Images of cracked and non-cracked bridges were used to train the neural network. The images were converted to frequency domain before being input into the neural network algorithm. The developed neural network algorithm has an accuracy of 99.25% [4].E.I.Shifrin and I.M. Lebedev performed a numerical simulation of a beam with multiple cracks. The transverse open crack was modelled as a massless spring. The beam with crack is simulated as fourth order ordinary differential equation. Conversion of the ordinary differential equation into an inverse spectral problem. Efficient identification of multiple cracks using natural frequency data [5].G. Sha et al. developed a finite element model of a beam. The crack inside the beam was considered as an element with reduced stiffness. The severity of the crack was changed by varying the stiffness reduction ratio. The first four vibration modes were analysed. Crack location and severity were determined based on the natural frequency and mode shapes [6]. M.T. Das et al. investigated the natural frequencies of a composite beam. The free vibration of a curved composite beam was analysed numerically and experimentally. It was found that the natural frequency decreases as the depth of the crack increases. When the crack is away from the fixed support, the natural frequency increases. The amplitude of vibration was observed before and after crack formation [7]. V. Khalkar and S. Ramchandran carried out an analysis of free vibration of a beam with crack. They observed the effect of crack location, crack severity and crack geometry on the stiffness of the cantilever beam. The change in stiffness of the beam due to a V-shaped, U-shaped and rectangular crack was compared. Finite element model of the beam with crack analysed. Crack detection using free vibration to determine crack location and severity. The results obtained by free vibration method accurately identify the location of the crack [8]. M Nikoo et al. modelled ANN, to determine the natural frequencies of a beam. The load on the beam, the length of the beam and the moment of inertia were entered into ANN. ANN was trained by inputting 100 measurements of known power. It was found that the model ANN trained with genetic algorithm accurately finds the natural frequencies of the beam [9]. S. Khatir et al. constructed an experimental setup to determine the location of damage and its severity. The natural frequencies of the beam were determined both experimentally and numerically. The crack produces local flexibility within the beam. Matlab programme used to identify the crack location and severity. The developed algorithm was validated against experimental results. After completion of training, the developed algorithm gives accurate results [10]. Abhijeet S. Tate et al. performed a finite element analysis of a beam using ANSYS software. Mode shapes and natural frequencies were obtained from finite element analysis of a beam with crack. Vibration analysis of the shaft was performed using Fast Fourier Transform. Since the crack is near the fixed beam, the natural frequencies of the shaftwere reduced. Crack location and severity were accurately determined using finite element method [11]. M. Dahak et al. used the frequency contour method to determine the crack location and severity in the shaft. The contour line is drawn from the change in natural frequency of the shaft. The shape of the curvature mode was calculated numerically. The obtained results were experimentally validated by an impact hammer test. In this method, it is not necessary to create a model of a beam. Crack prediction using a low-cost experimental setup [12].

M.J. Gomez et al. used vibration signal analysis to find cracks in railway axles. Vibration signals were obtained by varying the crack depth. The obtained vibration signals were used to train ANN. Defects with larger crack depth were identified with 100% accuracy. Wavelet packet transform is used to process the vibration signals. The energies of the wavelet packets were used as input to ANN [13]. F.E. Gunawan et al. developed a damage indicator to identify structural cracks. The damage indicator monitors system parameters such as mode shapes, natural frequencies, strain energy etc. The damage indicator was developed using Euler-Bernoulli beam theory. Numerical model of a cracked beam developed. Change in eigenmodes and natural frequencies observed. Results of damage indicator model are compared with experimental results. Damage indicator accurately determines the location and severity of damage [14]. Y Wang et al. developed a finite element model of a cracked Euler-Bernoulli beam. The free vibration method was used for damage detection. The mode shape and natural frequencies of the Euler-Bernoulli beam were obtained using the numerical method. The numerical results were validated using the results of experiments. The proposed method finds the damage location accurately [15]. Hussein I Mansoor et al. observed vibration parameters of rotor shaft to identify cracks. The natural frequencies of the gas turbine shaft and vibration characteristics were analysed. The turbine rotor was modelled experimentally. Critical speed of the shaft without crack and with crack observed. The critical speed of the shaft was reduced by the crack. The amplitude of vibration increased as the crack depth increased [16].

Lourdes Rulao et al. studied the crack behaviour in the shaft using antiresonance frequency data [17]. M.J. Gomez et al. identified the presence of a crack in the shaft based on the vibration behaviour of the shaft [18]. Anuj Kumar Jain et al. used an impact hammer test to determine the natural frequencies of the shaft. The severity of the crack was determined based on the natural frequencies [19]. Alok Ranjan Biswal et al. observed the natural frequency and amplitude of vibration of the shaft. A governing equation for the cracked shaft was developed [20]. Sandeep Das et al. predicted the lifetime of a shaft by analysing the dynamic behaviour of a shaft. They observed the effect of the presence of a crack on the natural frequency and amplitude of the vibration [21]. S.K. Sahu and P. Das carried out a numerical and experimental study of cracked shaft using natural frequency technique [22]. Dinesh Satpute et al. used the finite element method to determine the first three natural frequencies. It was found that the crack can be identified efficiently with the help of natural frequencies [23]. A.P. Bovsunovsky used the change in shaft compliance to identify crack properties [24].

Youngfeng Yang et al. developed a finite element model of the shaft with transverse crack. Harmonic balance method was used to identify crack in the shaft [25]. Hamid Khorrami et al. developed a mathematical model of a shaft with a transverse crack. The critical speed and lateral behaviour of the shaft depend on the position of the crack and its severity [26]. DebendraGayen et al. observed the critical velocity and natural frequency of the shaft by changing the depth of a crack. They developed a mathematical model of a shaft with transverse crack [27]. D. Koteswara Rao et al. compared a steel shaft with a functionally stepped shaft. Rotating shaft efficiently modelled with F.G. shaft [28]. Vinod Bansode et al. developed an analytical and experimental method for detecting cracks in rotating shaft [29].

1.5 Summary of Literature

The hybrid crack detection technique outperformed the other methods in finding cracks. The detection of cracks on different surfaces is facilitated thanks to this breakthrough in crack detection technology, which should lead to better results in the future.

1.6 Methodology

Figure 1 shows a shaft with bearings 1 and 2. A single crack occurs at an overhanging part of the shaft. Four crack locations i.e. 75, 150, 220 and 300 mm. A single crack with crack depth of 3 mm, 5 mm and 7 mm. The combination of four crack locations and three crack depths results in 12 individual crack values.

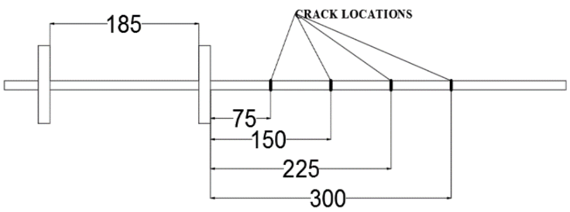

Fig. 1 Crack locations on the shaft

Figure 2 shows the flow of the methodology for the present work. The 3D models of the shaft CAD were created using CATIA software (see Fig. 3). Table 1 shows the combination of crack depth and crack location. These CAD models are imported into ANSYS software to perform the modal analysis. meshing of all CAD models was performed using ANSYS mesh generation utility. Natural frequency values determined by ANSYS. ANSYS frequency measurements of the natural phenomena. It was found that the first three mode shapes had an elongated shape. The mode shapes yielded the first three natural frequencies. The experiment with the whirling of the shaft yielded the critical speed. The natural frequencies and the critical speeds served as input to the artificial neural network. Crack location and crack depth of the shaft were predicted using ANN.

Table 1: Crack depth and crack location

Crack depth (mm)	Crack location from bearing 2 support			
3	75	150	225	300
5	75	150	225	300
7	75	150	225	300

1.7 Flow chart of the Research Work

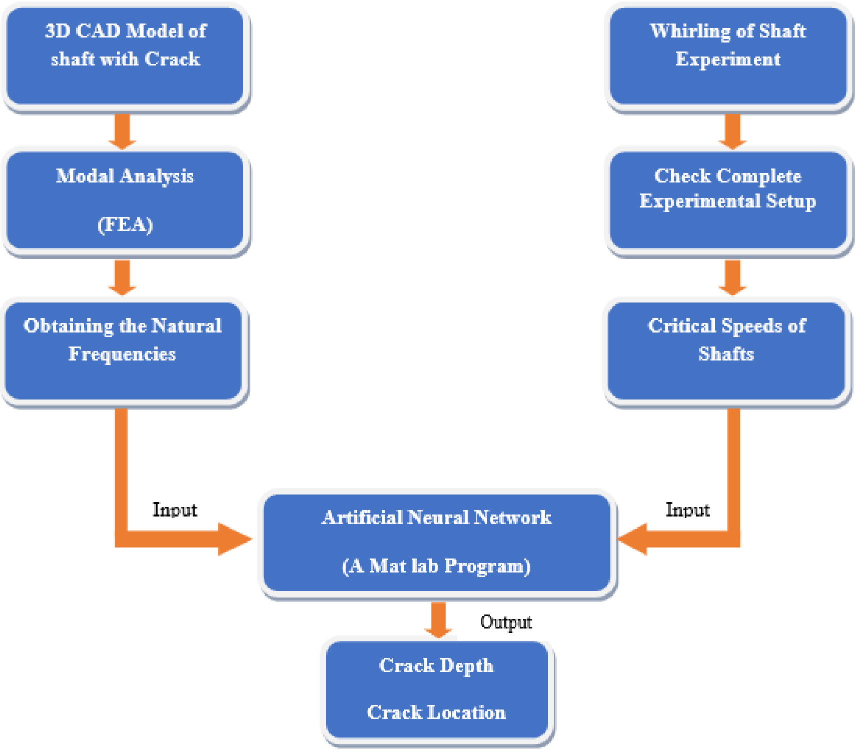

Fig. 2 Methodology to predict crack location and severity

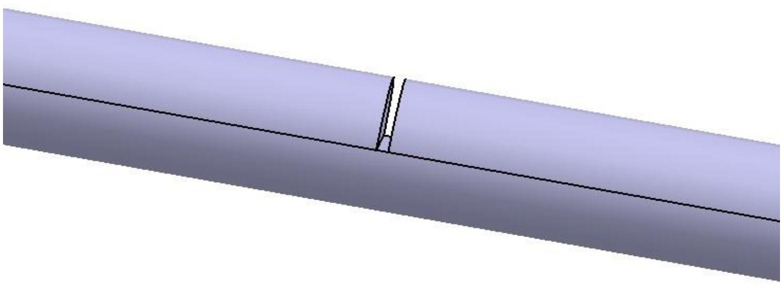

Fig. 3 CAD model of the shaft with crack

1.8 Experimental Work

To determine the critical velocities of shaft, experiments were carried out with the whirling of shaft. Various crack depths and cracks were placed unevenly on the shaft as shown in Fig. 1. The experimental setup consists of a shaft held between two bearing supports. An electric motor drives the shaft through a pulley. A single crack was created at the overhanging part of the shaft. The position of the crack is measured from the bearing support. A variable voltage drive is used to change the speed of an electric motor. Thus, it controls the speed of shaft rotation. Tachometer used to measure the RPM of the shaft. Figure 4 shows the experimental setup used for shaft rotation.

A shaft with a crack location of 75 mm and a crack depth of 3 mm was loaded into the experimental setup. The velocity of the shaft gradually increases from a stable position to the maximum RPM. At a certain velocity, the shaft starts vibrating with maximum amplitude. This speed of the shaft is called the critical speed of the shaft. Further increase in speed reduces the amplitude of vibration. The speed of the shaft is reduced and brought to a steady position. The crack depth is increased from 3 mm to 5 mm. The same procedure is repeated to find the critical speed.

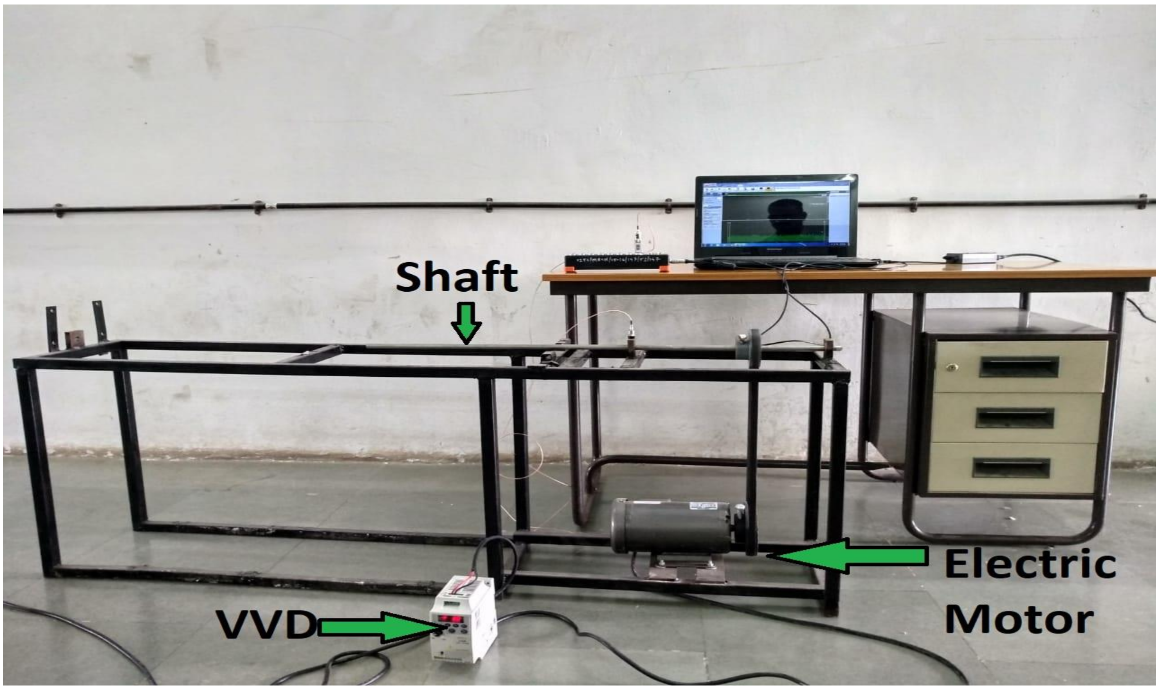

Fig. 4 Whirling of the shaft experimental set up

The crack depth was increased to 7 mm and the critical speed was measured. After 3 crack depths, the shaft is replaced by a new shaft with a crack position of 150 mm and the critical velocity was noted for crack depths 3 mm, 5 mm and 7 mm. The same procedure was repeated to find the values for 225 mm and 300 mm crack length.

1.9 Finite Element Method

CAD model of a shaft with crack prepared using CATIA V5 software and is shown the above figure. Combination of 4 crack location and 3 crack depths used to prepare the CAD model. Total 12 cad models generated.

The meshing of a shaft done with a tetrahedral mesh. In meshing, the shaft was divided into 106434 tetrahedral elements. Boundary conditions were applied to each small element. The results of all the elements were combined to obtain an output for the shaft. Figure 5 shows the meshed model of the shaft. Modal analysis to determine the mode shapes and natural frequencies of the shaft. The crack depth and crack position were predicted using artificial neural network. Training of ANN was performed with known output data. Four inputs were given to ANN, namely the first three natural frequencies of the shaft and the critical speed of the shaft.

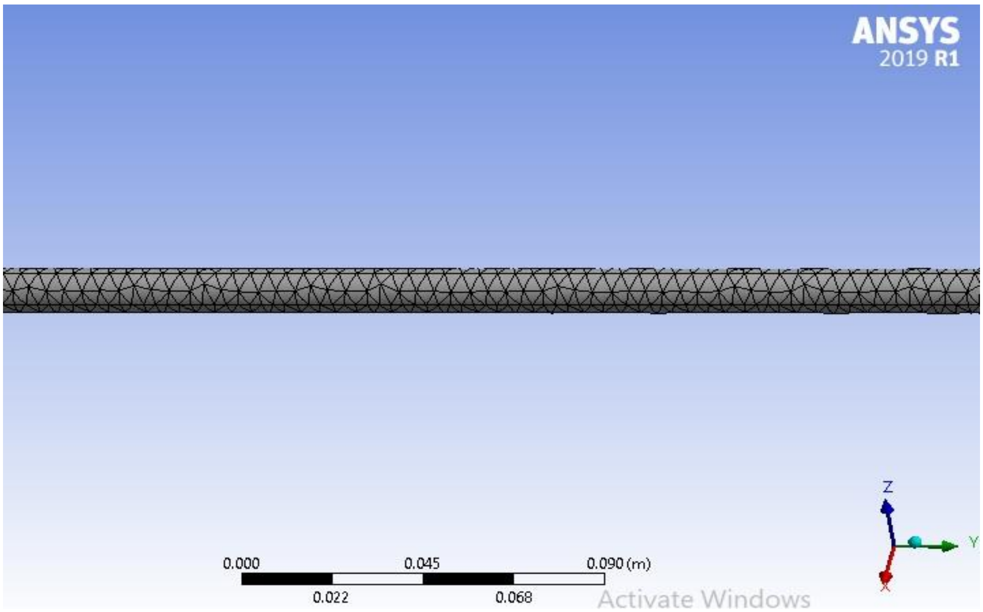

Fig. 5.Meshed Model of the shaft with a crack

1.10 Artificial Neural Network

To find cracks, scientists use a variety of time-honored techniques. Artificial neural networks (ANNs) have been one of the methods used. These inputs are processed by input layers of neurons. Each neuron is a mathematical function. The output of the input layer was passed to the middle layer through channels. Each channel has a specific weighting. The output of a previous layer was multiplied by the weight assigned to a channel and passed as input to the neuron of the next layer. Each layer has an activation function. The input of a neuron was passed to the activation function, which gives the output 0 or 1. If the value is 0, the neuron stops functioning and does not participate in the further operation of a neural network. When the value is 1, the neuron participates in the operation of the network. Crack depth and location are the output of a neural network. This output was compared with the known output to get an error. The error of ANN is reduced by managing the weights of a channel to get accurate readings. Figure 6 shows the basic structure of an artificial neural network used to determine crack properties.

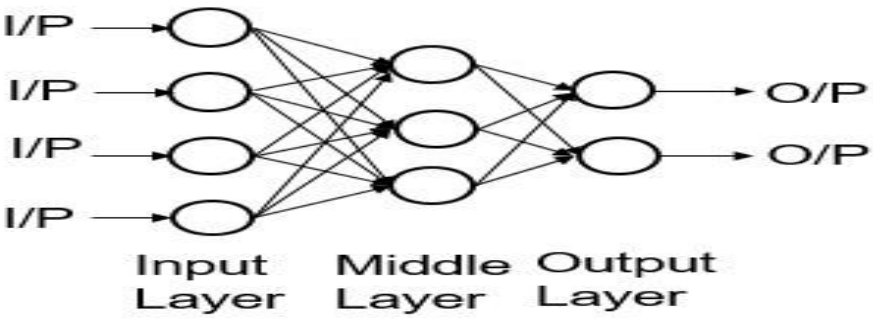

Fig. 6 Artificial neural network structure

1.11 Results& Discussions

Section 1.11.1 explains the results of the Whirling of shaft experiment. The results of the finite element method are explained in Section 1.11.2 and Section 1.11.3 describes the results of the artificial neural network.

1.11.1The Critical speed of a shaft

Table 2 shows the critical velocity obtained from the whirling of shaft experiment. Crack properties were determined from the critical speed of a shaft. Figure 7 shows the diagram of critical speed as a function of crack depth and crack position.

Table 2 Critical speed of shaft

Crack depth (mm)	Crack location (mm)	Critical speed of shaft (rpm)
3	75	1381
5	75	1302

7	75	1256
3	150	1346
5	150	1267
7	150	1204
3	225	1289
5	225	1211
7	225	1173
3	300	1215
5	300	1163
7	300	1109

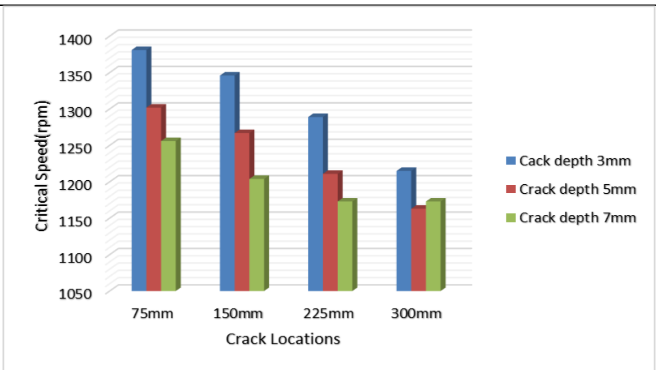

Fig.7 Critical speed of shaft

Table 2 shows the critical velocities of shaft at different crack depths. This table 2 shows that the critical speeds of the shaft decrease as the distance between cracks increases. As shown, the highest speed of the shaft is found at 1381 RPM when the crack spacing was about 75 mm. However, at a speed of 1109 the distance between the cracks is 300 mm. This shows that there is a proportional relationship between the speed of the shaft and the distance between the cracks. The above figure 7. shows the graphical representation between the critical speed and the crack locations. From this it can be seen that the crack location at 75 mm has the highest speeds of the shafts and hence reduces the value for other crack locations. As cracks remove material from the shaft, the stiffness of the shaft decreases around the crack. The stiffness of the shaft decreases in direct proportion to the crack depth. As a result, the critical speed of the shaft decreases as the crack depth increases.

1.11.2Mode Shapes

A mode shape is a deflection pattern associated with a particular natural frequency. The mode shape depends on the geometry of the object. The first three mode shapes were determined using the finite element method for a shaft with cracks. The first three mode shapes represent the first three natural frequencies of the vibration. Figures 8, 9 and 10 show the first, second and third mode shapes of the shaft. These images also represent the three natural frequencies.

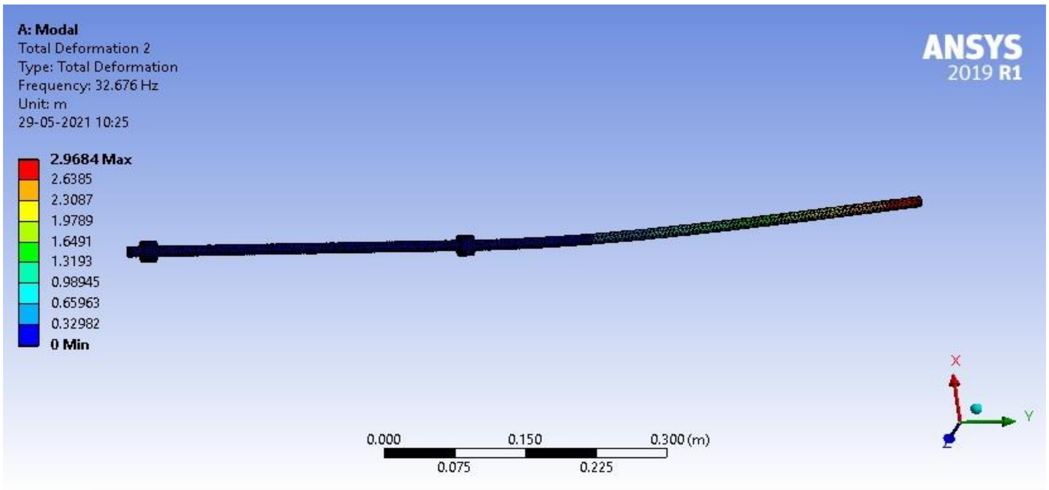

Fig. 8 First Mode shape of the shaft

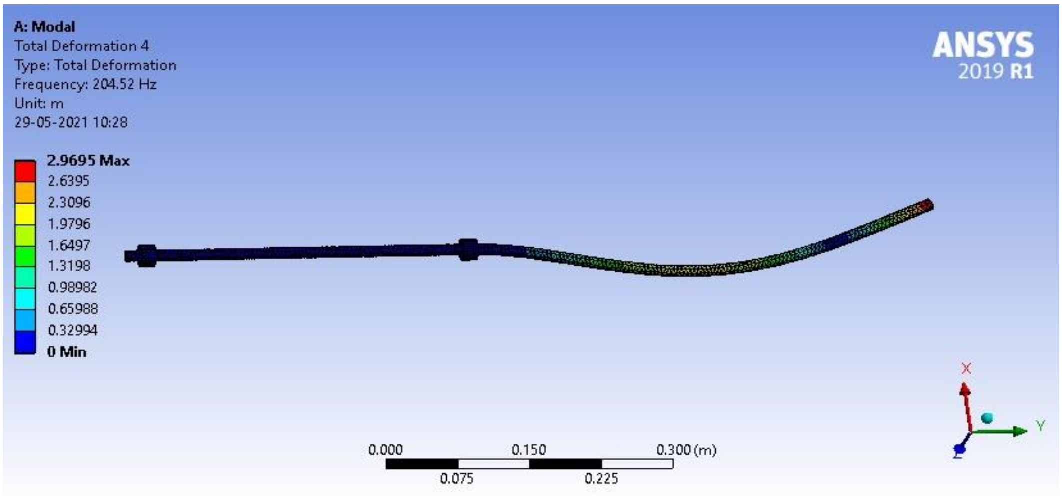

Fig. 9 Second mode shape of the shaft

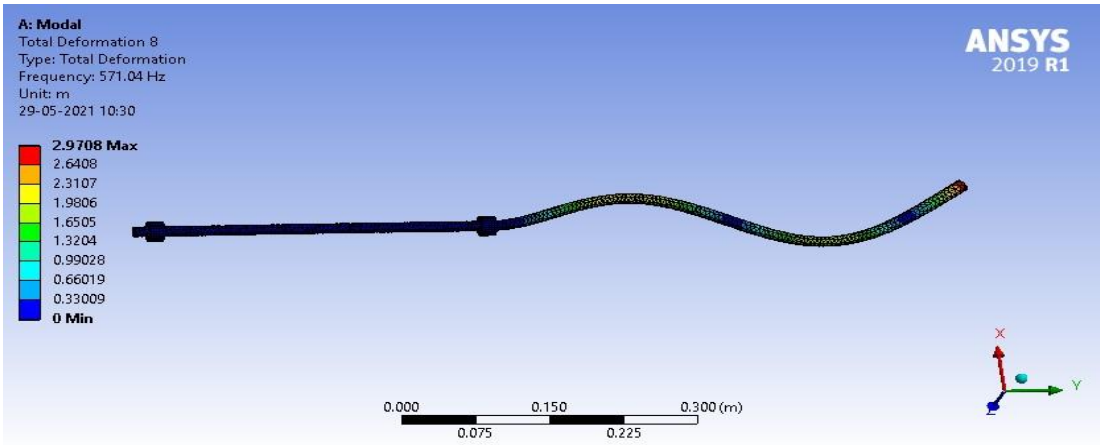

Fig. 10 Third mode shape of the shaft

The first, second, and third natural frequencies are 32.676, 204.52, and 571.04 HZ, respectively. The natural frequencies of the shaft were determined using the modal analysis technique in ANSYS Workbench. The finite element method was used to calculate the first three natural frequencies. The crack depth can be increased by decreasing the shaft frequency. The vibration of the shaft decreases as the crack moves away from the fixed support. This means that the natural frequency of a crack increases the farther it is from a fixed support. The combination of crack depth, crack position and the respective natural frequencies can be found in Table 3. Figure 11 shows the diagram of the natural frequency as a function of the crack position.

Table 3 First three natural frequencies

Crack depth (mm)	Crack location (mm)	First natural Frequency	Second Natural Frequency	Third Natural Frequency
3	75	33.52	185.17	465.21
5	75	30.17	183.15	454.22
7	75	25.18	176.32	443.17
3	150	36.16	183.13	479.23
5	150	32.42	181.12	465.22
7	150	27.83	178.14	454.78
3	225	38.3	191.89	452.75
5	225	33.93	187.79	443.21
7	225	30.16	185.13	433.54
3	300	39.12	202.06	461.28
5	300	36.12	198.56	453.18
7	300	29.91	193.21	446.61

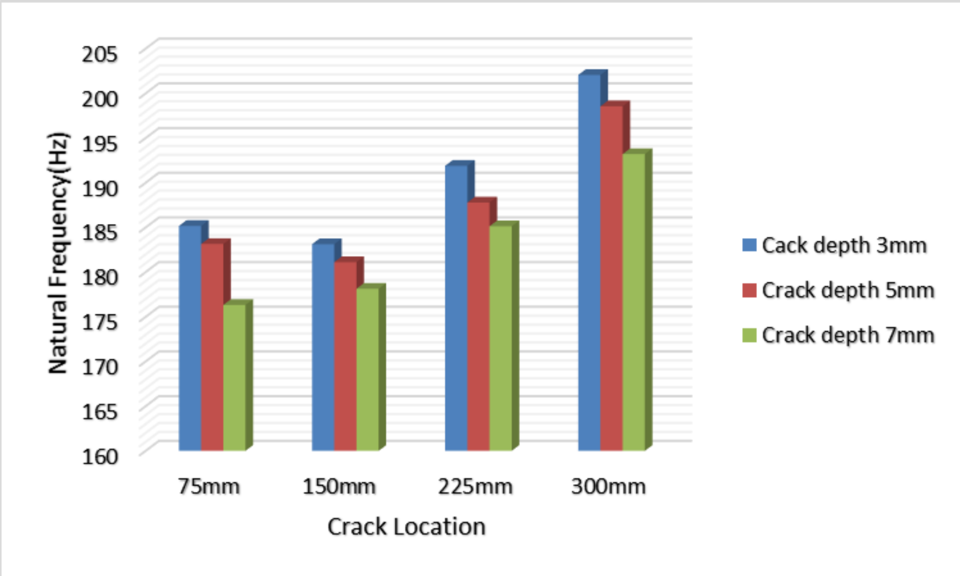

Fig.11 Natural frequencies of the Shaft

As can be seen in Fig. 11, as the natural frequency increases, the values of crack depth also increase. Based on the crack depths shown in Fig. 11, the natural frequency at 3 mm crack depth was high compared to the other two values. The natural frequencies of crack depths 5 mm and 7 mm also increase continuously, so that the vibrations in the shaft increase and the cracks eventually cause the shaft to break.

1.11.3Outcome of Artificial neural network

ANN first determine the result using the feed forward method. Compare the result with the known input result. ANN maintains the weights of the channel and tries to reduce the error between the feed forward results and the input results. After training is complete, the weights were adjusted to provide accurate results. After training, ANN gives results with negligible error rate.Matlab program prepared for ANN. The natural frequencies and critical speed were entered as input to ANN. Once the training of ANN is completed, it gives accurate results for the given inputs. Table 4 shows the input of ANN and the output of ANN.

Table 4 Output obtained from ANN

Input to ANN				Output from ANN	
First Natural Frequency(Hz)	Second Natural Frequency(Hz)	Third Natural Frequency(Hz)	Critical Speed (rpm)	Crack Depth (mm)	Crack Location (mm)
33.52	185.17	465.21	1381	3.001	75.002
30.17	183.15	454.22	1302	4.998	74.999
25.18	176.32	443.17	1256	7.002	75.002
36.16	183.13	479.23	1346	2.999	150.001
32.42	181.12	465.22	1267	5.001	149.999
27.83	178.14	454.78	1204	6.999	150.001
38.3	191.89	452.75	1289	3.002	225.001
33.93	187.79	443.21	1211	5.002	225.002
30.16	185.13	433.54	1173	6.999	224.999
39.12	202.06	461.28	1215	2.999	300.001
36.12	198.56	453.18	1163	5.001	299.998
29.91	193.21	446.61	1109	6.999	300.002

1.12 Conclusions

In the present work, a novel method for crack location and crack depth prediction was developed. Preparation of an experimental setup for the whirling of shaft. The critical speed was determined using the experimental setup. It was found that the critical speed decreases as the crack depth increases. Creation of cad models of the shaft with a single crack. Analysis of mode shape and natural frequency of the shaft with crack carried out using finite element method. The first three mode shapes were observed. The natural frequencies of the shaft were obtained from the modal analysis of the shaft. It was found that the natural frequency of the shaft decreases when the depth of the crack was greater. Matlab program prepared for ANN. The inputs were given to train ANN against known output. After training, ANN accurately predicts the crack position and crack depth. The following points can be included in future research work.

- There is a proportional relationship between the critical speed of the shaft and the distance between cracks.
- It was found that the crack location at 75 mm has the highest shaft velocities and thus the value decreases.
- The stiffness of the shaft decreases in direct proportion to the crack depth. Consequently, the critical speed of the shaft decreases as the crack depth increases.
- The first, second and third natural frequencies were 32.676, 204.52 and 571.04 HZ, respectively.
- The crack depth can be increased by decreasing the shaft frequency.
- The natural frequencies at crack depth of 5 mm and 7 mm increase continuously, where the vibrations in the shaft increase and the cracks cause the shaft to break.
- The combination of modal parameters such as mode shapes and modal damping is used to train ANN.
- The experiment was performed with multiple cracks at once, so ANN can be trained to detect multiple cracks on the shaft.
- With a higher number of crack measurements, ANN is trained to be more accurate.

1.13 Limitations of the Study

This limitation one should work on to improve performance of method used.

1. The output may vary depending on the complexity of the data provided.
2. Crack detection needs further study to make it more adaptable.
3. A highly skilled operator is required to ensure that the data obtained by this method is accurate.

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