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Prediction of Coast Down Time for Mechanical Faults in Rotating Machinery Using Artificial Neural Networks

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***Abstract*—**Misalignment and unbalance are the major concerns in rotating machinery. When the power supply to any rotating system is cutoff, the system begins to lose the momentum gained during sustained operation and finally comes to rest. The exact time period from when the power is cutoff until the rotor comes to rest is called Coast Down Time. The CDTs for different shaft cutoff speeds were recorded at various misalignment and unbalance conditions. The CDT reduction percentages were calculated for each fault and there is a specific correlation between the CDT reduction percentage and the severity of the fault. In this paper, radial basis network, a new generation of artificial neural networks, has been successfully incorporated for the prediction of CDT for misalignment and unbalance conditions. Radial basis network has been found to be successful in the prediction of CDT for mechanical faults in rotating machinery.

***Keywords*—**Coast Down Time, Misalignment, Unbalance, Artificial Neural Networks, Radial Basis Network.

I. Introduction

SHAFT misalignment and unbalance are the most common causes of vibration in rotating machinery and these are the major concerns in modern industry. Misaligned shaft leads to increase in vibration, and an increase in radial and axial loads, thereby absorbing more energy and power. This, in turn, causes premature wear or even catastrophic failure of bearings, seals, coupling and other components in the machinery. Shaft misalignment occurs when the centerlines of rotation of two or more machinery shafts are not in line with each other, or in more precise terms, it is the deviation of relative shaft position from a collinear axis of rotation measured at the points of power transmission when equipment is running at normal operating conditions. There are two types of misalignments: Parallel misalignment occurs when the shaft centerlines of the two machines are parallel, but offset to each other, and Angular misalignment occurs when the shaft centerlines are not parallel, but inclined to each other [1]. Unbalance is a condition where the center of mass (rotor disc, blower impeller) is not coincident with the center of rotation (shaft). Excessive unbalance can lead to fatigue of machine components, as well as can cause wear in bearings or internal rubs that can damage seals and degrade machine performance [2]. In practice, achieving perfectly aligned and balanced condition is very difficult and a minute amount of misalignment and unbalance are always present.

When the power supply to any rotating system is cutoff, the system begins to lose the momentum gained during sustained operation and finally comes to a halt. The behavior of the rotor system during this period is known as the Coast Down Phenomenon (CDP). The exact time period between the power cutoff time and the time at which the rotor stops is called Coast Down Time (CDT) [3]. CDT is the total time taken by the system to dissipate the momentum acquired during sustained operation. The CDT depends on many factors like inertia forces of the system components, tribological behavior of rotating system components such as bearings, seals, carbon brushes. It also depends on operating conditions and environmental effect such as fluid drag. The performance of the misaligned cylindrical [4] and three-lobe journal bearings [5] were evaluated. It was found that the CDT decreases with the increase in misalignment. This is because both the bearing friction and the power loss increase with increase in misalignment. Increase in misalignment will cause an increase in coefficient of friction and reduces the film thickness resulting in an increase in damping factor. Some published works [6], [7] have reported experiments conducted on rotor system to evaluate the bearing lubrication for different operating conditions and the influence of the rotor unbalance response on CDT. It was found that CDT could be used as an effective diagnostic parameter and could provide pertinent information regarding the tribological behavior, degradation and the effectiveness of lubrication.

All these studies were conducted on De Laval (Jeffcott) rotor system supported between two bearings. An industrial environment to assess the CDT as a condition monitoring parameter was considered and an attempt was made to experimentally investigate the use of CDT analysis in a Forward Curved Centrifugal Blower [8]. This work was carried out to assess the effect of misalignment and unbalance for understanding the mechanical behavior of a system under simulated industrial environment. It was found that with

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increased mechanical faults, CDT decreases considerably and this is expressed as CDT reduction percentage. There is a specific correlation between the reduction percentage in CDT and the level of unbalance, and the order of offset and angular misalignment with rotational speeds. And the mechanical fault has the considerable influence on CDT reduction percentage. CDT analysis is a powerful parameter for studying the significant machine's health. It could be used as a powerful diagnostic tool for condition monitoring of rotating machinery.

Artificial neural network is a representation of the computational architecture of the human brain. It is an established tool for effortless computation and its application in the area of automated fault detection and diagnosis of machine condition is very promising [9]-[12]. The time-domain vibration signals of rolling bearings with different fault condition are pre-processed using Impulse and Laplace wavelet transforms. The extracted features for the predominant wavelet transform coefficients in time and frequency domain are applied as input vectors to artificial neural networks for rolling bearing fault classification. The ANN classifier parameters (learning rate and number of hidden nodes) are optimized using a genetic algorithm [13]. The multi layer feed forward backpropagation techniques were used to detect bearing faults [14]-[16]. Several methods are described [17] for the extraction of features to use as neural network inputs and compares these methods based on measuring the zero lag higher-order statistics of the measured vibration time series and achieved success rate of over 99 percent. Genetic Algorithm is used to select the most significant input features from a large set of possible features in machine condition monitoring. Used a large set of 156 different features and found that, the GA is able to select a set of 6 features that gives 100 percent recognition accuracy [18]. Radial basis networks require lesser neurons than the standard feed forward backpropagation networks [19]-[21]. They can be trained in a fraction of time is used to model engineering systems and found that it is efficient, reliable and robust technique [22].

The CDT analysis can be used as one of the condition monitoring parameter to assess the condition of the rotating machinery. From the survey of literature and to our best knowledge; the application of ANN is not extended to CDT prediction. The main objective of this paper is to develop neural network model that will be able to predict the CDT for mechanical faults.

II. Experimental Test Rig And Instrumentation

The schematic diagram of experimental Centrifugal Blower test rig [23] used for this investigation is shown in Fig. 1. A Forward Curved (FC) centrifugal blower is mounted on shaft with length 315 mm and diameter of 20 mm at the center position of 190 mm between two anti-friction bearings. The specifications of the blower are given in Appendix A. The shaft is simply supported between two Z type SKF antifriction ball bearings. The blower shaft is connected through an electromagnetic coupling to a variable speed DC motor (operating speed 3000±5% rpm). Motor side shaft is supported by one each Z type and P Block (self aligning) bearing. An adjustable steel plate of size 400 mm x 300 mm x 15 mm has been introduced on which the blower setup and two bearings housing frames are bolted to introduce the required parallel and angular misalignment between the blower shaft and motor shaft. This assembly is mounted on the main heavy steel frame with adjustable four screws at four corner ends of the steel plate and a lead screw at the bottom, for horizontal movement. The contact surface of steel plate assembly and main steel frame are perfectly flat and smooth for accuracy. The whole test rig unit is mounted on a heavy steel framework, and then the framework is clamped to a foundation with anti vibration rubber pads. An instrumentation control panel is built to display and control the variables. Two inductive proximity sensors are used to measure the speeds of blower and motor independently.

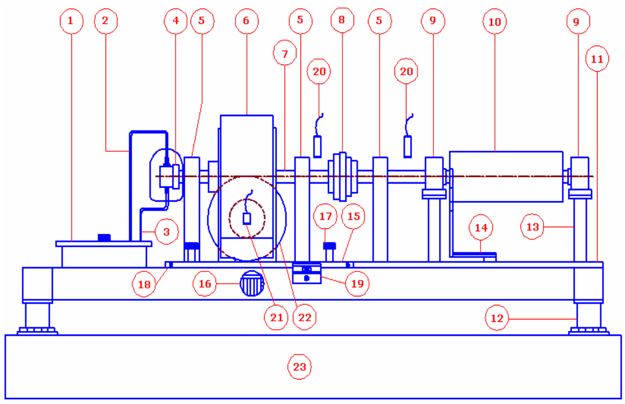

Fig. 1 Centrifugal Blower Experimental Test Rig

1, Oil sump fitted with motor; 2, Oil entry hose pipe; 3, Oil exit hose pipe; 4, Journal bearing; 5, Z Type Ball Bearings; 6, Forward Curved Centrifugal Blower; 7, Shaft; 8, Magnetic coupling; 9, Self aligning P Block Bearings; 10, Variable Speed DC motor; 11, Supporting structure; 12, Clamping screws; 13, Motor supporting frame; 14, Load cell; 15, Misaligning adjusting steel plate; 16, Plate movement screw (lead screw attachment is not shown) ; 17, Four screws for vertical direction adjustment of steel plate; 18, Two leveling support bars; 19, Digital Vernier caliper; 20, Proximity switches; 21, Hotwire Anemometer; 22, Butterfly Valve; 23, Concrete base.

The Visual Basic application software developed along with instrumentation is used to control the operation of experimental test rig and to record the motor, and blower speeds as well as CDT for each test run for selected cutoff speeds. During start of test run, the system automatically cuts off the power supply to motor and magnetic coupling simultaneously so that the blower shaft completely disengages from motor shaft. At the end of the test, the power supply is restored for both motor and coupling such that they run continuously. Software has an ability to record CDT with an accuracy of 0.06 s (60 ms) intervals and corresponding deceleration speed of blower and motor.

III. Experimental Procedure

The blower shaft and motor shaft are carefully aligned and balanced in both vertical and horizontal directions using reverse dial indicator method. An electromagnetic coupling was used to ensure that the entire centrifugal blower system is completely free from the power source during coast down period test run. This is to minimize the effect of external disturbance due to the fluctuation in power source voltage, frequency, etc that can have an appreciable effect on CDT. Initially, the coast down time for each test run at various cutoff speeds were recorded and used thereafter as baseline references for further investigation, analysis and comparison.

Parallel misalignment in vertical and horizontal direction was introduced using four screws and a lead screw. The possible movement of the steel plate in other directions can be restricted by means of level bars supported with steel balls support. A digital Vernier Caliper is attached to the steel base plate to record the offset value. Three level of parallel misalignment 0.20 mm, 0.40 mm and 0.60 mm respectively have been introduced at the blower end shaft. Angular misalignment was introduced by creating the gap between the steel plate and main support frame by adjusting the screws in one direction and inserting shims of specific thickness between the gaps to lift it upward with respect to the main frame, and then the corresponding inclined misaligned angle was calculated. Three levels of angular misalignment 0.061^0, 0.0993^0, and 0.153^0 respectively have been introduced between blower and motor shaft end. Tests were conducted for three cases of unbalance by introducing additional mass of 22 gram-mm, 27 gram-mm and 32 gram-mm respectively. The masses have been added on blower impeller blade in the same location. All the experimental tests were conducted at cutoff speeds of 1000 rpm, 1500 rpm, 2000 rpm, and 2500 rpm respectively to record coast down time and the respective deceleration speeds. These experimental data are used to train an ANN to predict the CDTs for various mechanical faults.

The profile CDT curves, the speed in rpm versus CDT in milliseconds at higher cutoff speed of 2500 rpm for parallel, angular misalignment and unbalance conditions are shown in Figs. 2-4. The typical CDT curves are characterized by three zones, at the beginning of the coast down as a small convex shape, at the middle of the coast down as s concave shape and at the end of the coast down one more as a small convex shape. It was found that as malfunction progress the blower shaft comes to rest faster within a lesser time. This is due to the increased power loss and increased torque in the bearings which is once again due to increased malfunction. It has been observed that the slopes of the curves vary slightly from one another; higher energy dissipation takes place during the middle of the coast down. At higher speeds the CDT profile curves are much sharper and smooth when compared at lower speeds and these profile curves follows the frictional characteristic described by Raimondi & Boyd design curve [24]. Since the blower shaft is completely free from the driving shaft during the coast down period, as predicted, the blower shaft takes a longer time to dissipate the acquired energy during sustainable operation at higher running speeds. Consequently a higher CDT is obtained. The CDT reduction percentage was calculated in each case using the relation:

CDT reduction percentage =
[(baseline CDT-obtained CDT)/baseline CDT]*100

At lower cutoff speed with smaller faults, has no significant effect on CDT reduction percentage.

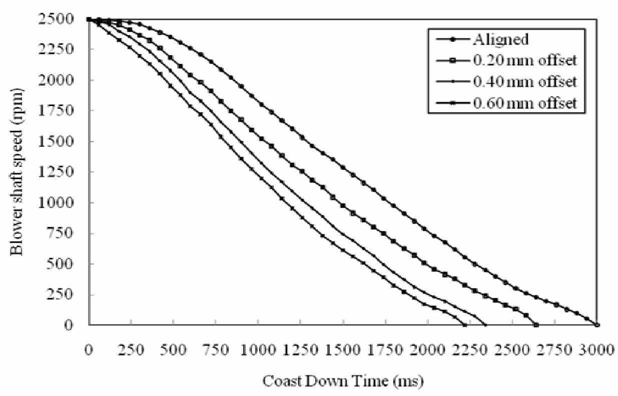

Fig. 2 CDT profile for parallel misalignment at 2500 rpm

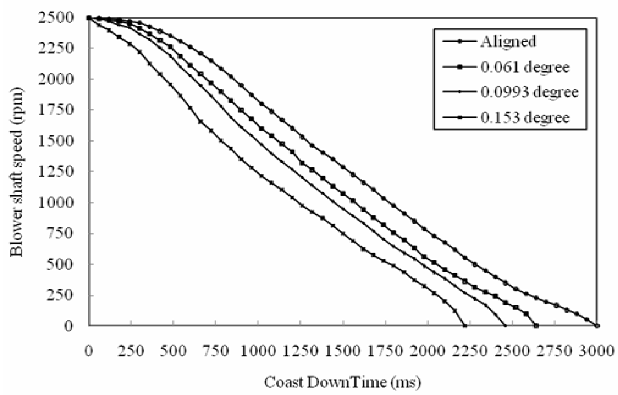

Fig. 3 CDT profile for angular misalignment at 2500 rpm

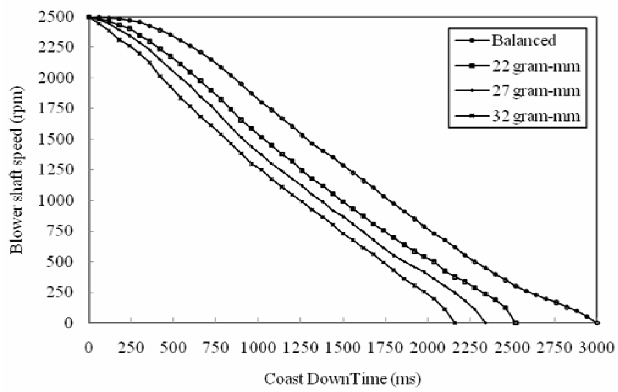

Fig. 4 CDT profile for unbalance at 2500 rpm

IV. Radial Basis Function Neuron Model

Radial Basis Function (RBF) networks form one of the essential categories of neural networks. A RBF network is a two-layer network whose output units form a linear combination of the basis functions computed by the hidden units. A function is radially symmetric (or is an RBF) if its output depends on the distance of the input sample (vector) from another stored vector. Neural networks whose mode functions are radially symmetric are referred to as radial basis function networks [25].

The general model of RBF neuron is shown in Fig. 5. The transfer function for a radial basis neuron is radbas. The radial basis neuron receives as net input, the vector distance between its weight vector w and the input vector p, multiplied by the bias b. The basis functions in the hidden layer produce a localized response to the inputs so that each hidden unit has a localized receptive field. The basis function can be viewed as the activation function in the hidden layer. The outputs of the hidden unit lie between 0 and 1. The closer the input to center of the Gaussian, the larger the response of the node. The node produces an identical output for inputs with equal distance from the center of the Gaussian; it is called a radial basis. The output unit finds a linear combination of nonlinear basis functions and thus the network performs a nonlinear transformation of the input.

RBF network is capable of approximating any arbitrary mapping. The main difference between the RBF network and the backpropagation network is in their basis functions. The radial basis function covers only small regions, whereas the sigmoid function used in neural network assumes nonzero values over an infinitely large region of the input space. Classification tasks are more amenable to the RBF network than the backpropagation network in the case when the problem is extended to higher dimensions [26].

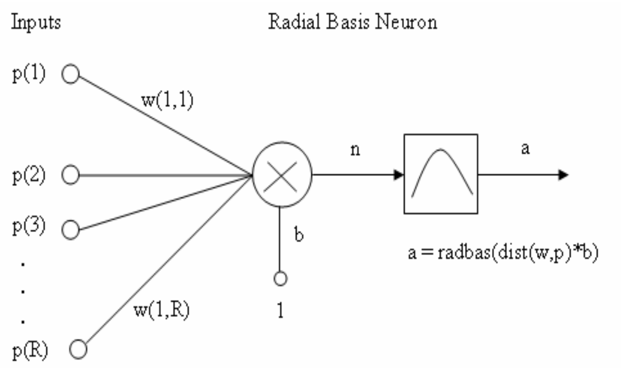

Fig. 5 Radial Basis Neuron Model

V. RBF Training Procedure

The radial basis neural networks have been designed by using the function newrb in the neural network toolbox supported by MATLAB [27]. The function newrb iteratively creates a radial basis network by including one neuron at a time. Neurons are added to the network until the sum of squared error is found to be very small or the maximum numbers of neurons are reached. At each iteration, the input vector, which will result in lowering the network error most, is used to create a radial basis neuron. During the training, each of the connecting weighs of the individual neuron is compared with the input signals. The distance between the connecting weights determines the output of hidden neurons and input vector, which is further multiplied by bias. Bias is an additional scalar quantity being added between the neuron and fictitious neuron. The output is propagated in a feed forward direction to the output layer neuron, which will give the output if the connection weights are close to the input signal. This output is compared with target vector. If the error reaches the error goal, then training is terminated, otherwise the next neuron will be added. The connecting weights are modified each time by changing the maximum neurons and the spread constant. The value of maximum neuron and spread constant keeps on changing till the network is trained properly. Radial basis networks can be used to approximate functions; newrb adds neurons to the hidden layer of a radial basis network until it meets the specified mean squared error goal.

VI. Radial Basis Neural Network In CDT Data Predictions

The input parameters were normalized before being applied to train and test the networks; the CDT data were normalized by dividing each time interval (60 ms) by CDT for normal and various faulty conditions. Normalized CDT values range from 0 to 1. Similarly, deceleration speed is normalized by dividing each deceleration speed by the cutoff speed for normal and various faulty conditions. Normalized speed reduction values range from 1 to 0. In the present work Radial basis function neural network is considered for predicting the CDT.

A.Parallel Misalignment

The RBF network was trained for the various levels of parallel misalignment conditions. From 27 CDT data points at various level of parallel misalignment, 21 data were used for training and the remaining 6 data were used for testing at 1000 rpm. From 32 CDT data points, 24 data were used for training and the remaining 8 data were used for testing at 1500 rpm. From 40 CDT data points, 30 data were used for training and the remaining 10 data were used for testing at 2000 rpm. From 44 data CDT data points, 33 data were used for training and the remaining 11 data were used for testing at 2500 rpm. Variation in number of data points for training and testing is due to higher CDT values at higher speeds. Fig. 6 shows the training procedure adopted by RBF for parallel misalignment. This plot shows error as a function of training epochs.

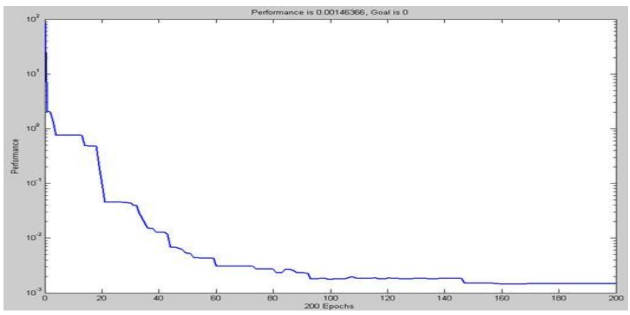

Fig. 6 ANN Training for parallel misalignment

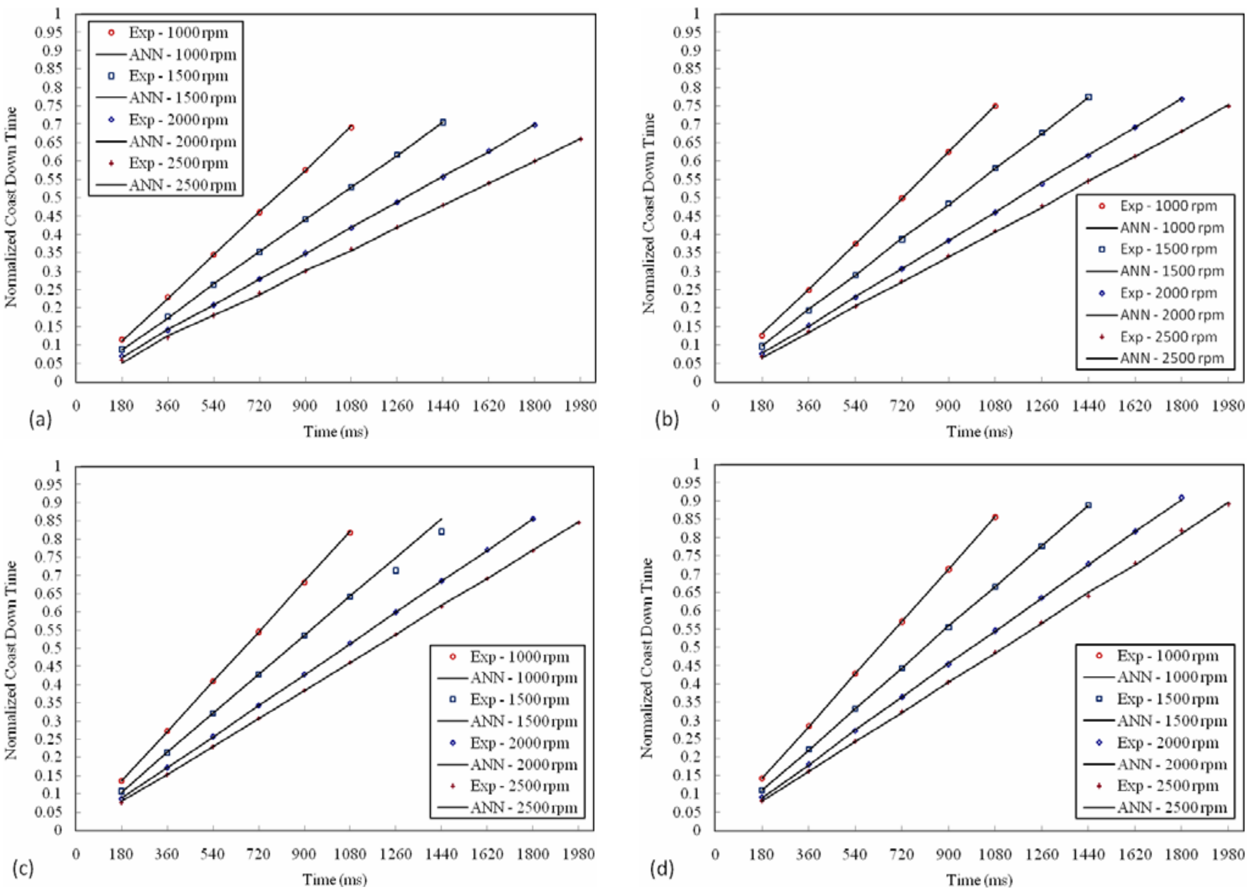

Fig. 7 Experimental and Artificial Neural Networks predicted CDT data for a) aligned, b) 0.20 mm, c) 0.40 mm and d) 0.60 mm parallel misalignment at blower shaft speed of 1000 rpm, 1500 rpm, 2000 rpm and 2500 rpm

The trained network was used to predict the CDT data at different cutoff speeds, at various offset distances, and the results were compared with the experimental values as shown in Fig. 7. Normalized CDT was used to plot, since this is more appropriate than using CDT values. These plots represent normalized CDT versus CDT test time intervals corresponding to the number of test data points for experimental and ANN predicted values.

B.Angular Misalignment

The RBF network was trained for the various orders of angular misalignment conditions with the same number of sets of data points used in parallel misalignment were used for training and testing under same shaft cutoff speeds. The trained network was used to predict the CDT data at different cutoff speeds and the results were compared with the experimental values as shown in Fig. 8.

C. Unbalance

The RBF network was trained for the various unbalance weights with the same number of sets of data points used in parallel misalignment were used for training and testing under the same shaft cutoff speeds. The trained network was used to predict the CDT data at different cutoff speeds and the results were compared with the experimental values as shown in Fig. 9.

VII. Results And Discussions

The radial basis function network was trained to predict coast down time. The CDTs and deceleration speeds are used to train and test the neuron to predict the CDT for different levels of mechanical faults. The neural network predicted data were compared with the experimental values at the coast down time intervals of 180-2160 ms. It has been observed that artificial neural network modeling of system based parameters are found to match closely with the experimental data at normal and at various mechanical faults conditions, the variation is around 1.29 percentages.

From the modeling, the results show that the distribution of experimental values and ANN predicted values are very close to each other in all the three cases. However, it is found that the deviation is slightly more at lower speeds for angular misalignment condition. At higher speed, the best prediction results are observed for all the three cases in various levels of introduced mechanical faults.

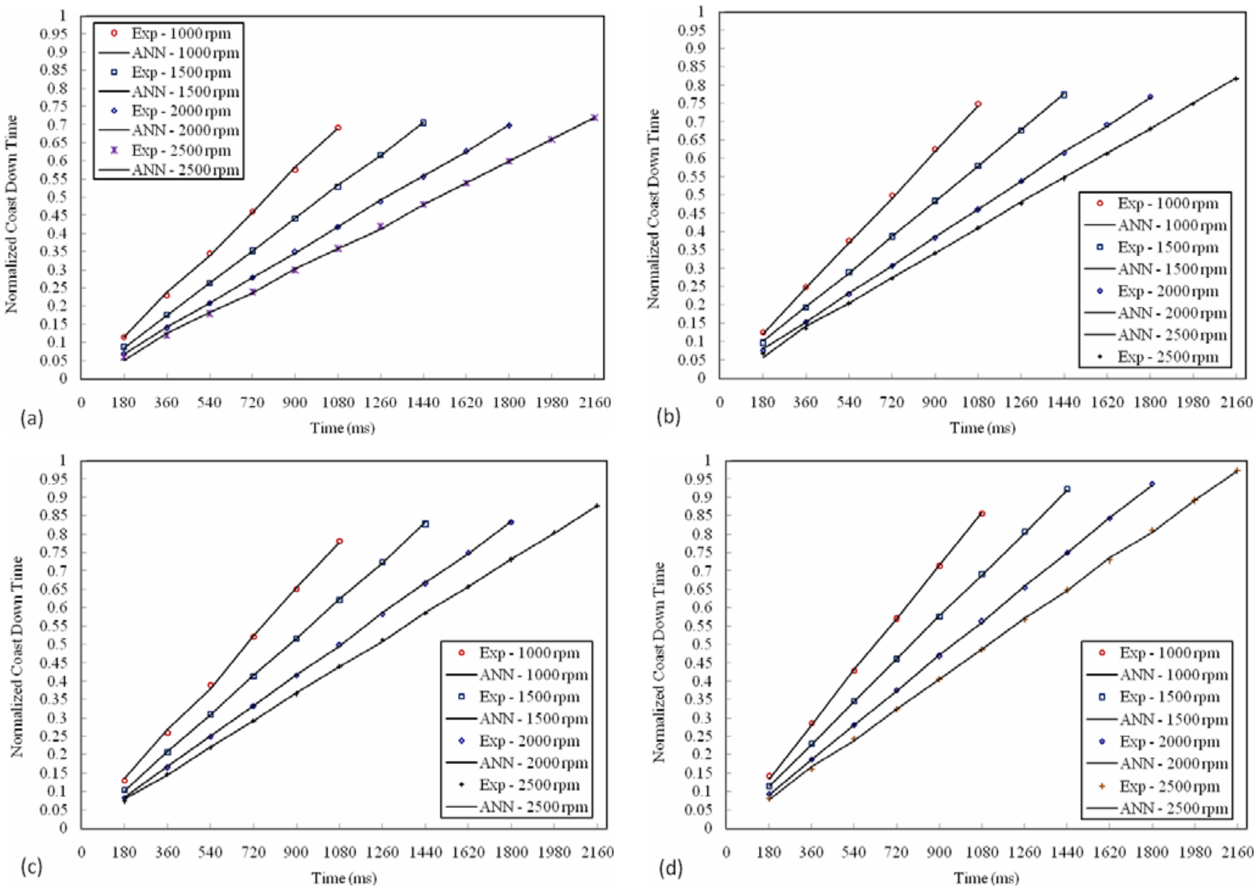

Fig. 8 Experimental and Artificial Neural Networks predicted CDT data for a) aligned, b) 0.061^0, c) 0.099^0 and d) 0.153^0 angular misalignment at blower shaft speed of 1000 rpm, 1500 rpm, 2000 rpm and 2500 rpm

By comparing the ANN predicted CDT values with experimental CDT values; artificial neural networks modeling of system is found to be satisfactory for predicting the CDT for parallel, angular misalignment and unbalance faults.

The absolute standard deviation and root mean square error [25] used in this study for the evaluation of differences between ANN and experimental values are defined as:

Absolute Standard Deviation:

$$\text{ABSD} = \frac{\sum |(ANN\ value - Experimental\ value)|}{\text{Number of data points}}$$

Root Mean Square Error:

$$\text{RMSE} = \sqrt{\frac{\sum \left(\frac{Experimental\ value - ANN\ value}{Experimental\ value} \right)^2}{\text{Number of data points}}}$$

The absolute standard deviation and root mean square error calculated for each fault at various cutoff speeds are tabulated in Table. 1. From these results, for all the three cases, it has been observed that the error values as described by ABSD, RMSE are well within the permissible limits. This proves the efficiency of the methodology adapted in this research. The absolute standard deviation for all the three cases is found to be very small which indicates that the ANN predicted CDT values are very close to experimental values. The root mean square error is an excellent criterion for evaluating the performance of the neural network used. The lower values of root mean square error indicates the best performance of the neural network in predicting the CDT for all the cases for various mechanical faults. Hence the ANN based prediction of CDT for mechanical fault in rotating machinery has been found successful and reliable. This work leads to a new dimension of using ANN as an effective tool to predict condition monitoring parameter. The artificial neural network modeling to predict coast down time is highly justified for the CDT analysis as one of the condition monitoring parameter to assess the condition of the rotating machinery.

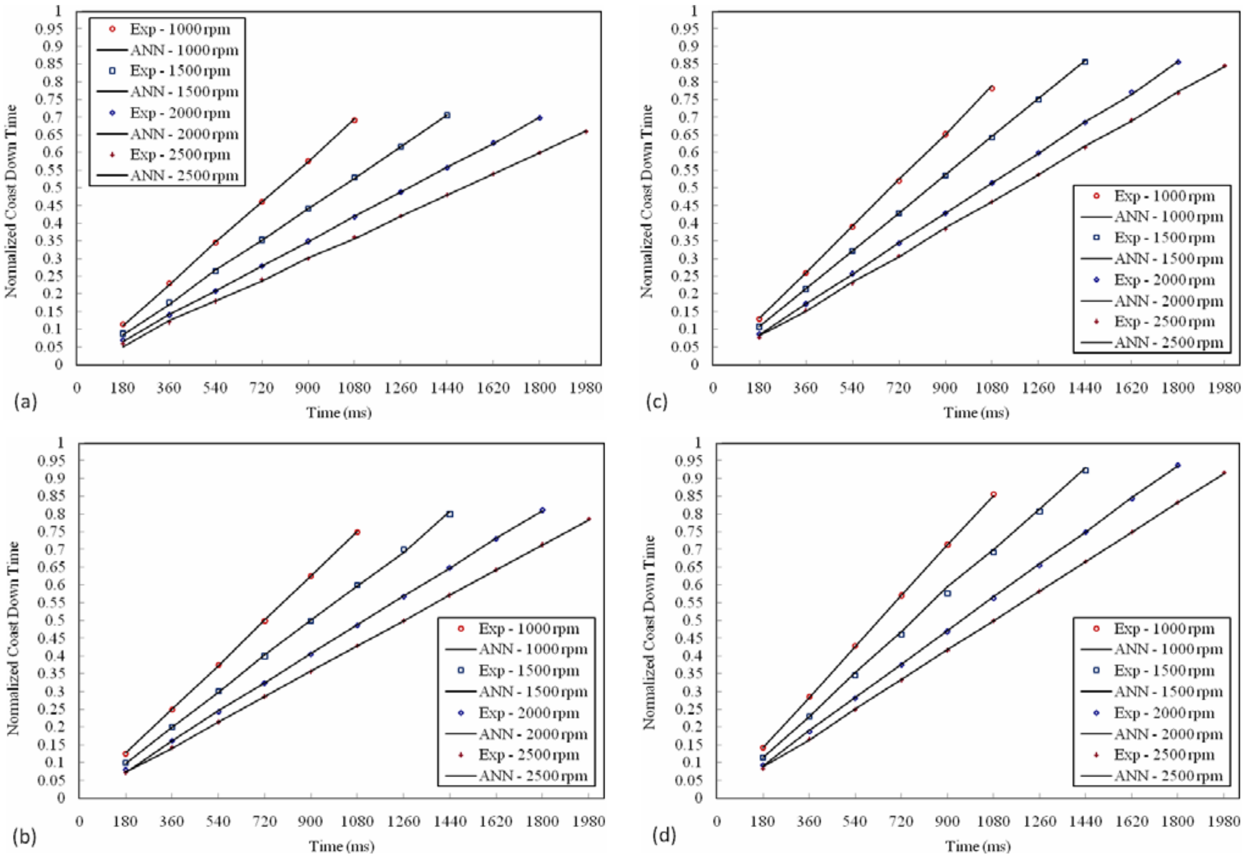

Fig. 9 Experimental and Artificial Neural Networks predicted CDT data for a) balanced, b) 22 gram-mm, c) 27 gram-mm and d) 32 gram-mm unbalance weights added at blower shaft speed of 1000 rpm, 1500 rpm, 2000 rpm and 2500 rpm

TABLE I
COMPARISON BETWEEN EXPERIMENTAL AND ARTIFICIAL NEURAL NETWORK PREDICTED CDT VALUES FOR MECHANICAL FAULTS

Mechanical faults	Cutoff Speeds rpm							
	1000 rpm		1500 rpm		2000 rpm		2500 rpm	
	ABSD	RMSE	ABSD	RMSE	ABSD	RMSE	ABSD	RMSE
Parallel Misalignment	0.00197	0.01436	0.00369	0.01559	0.00254	0.01943	0.00201	0.02694
Angular Misalignment	0.00498	0.02352	0.00215	0.01370	0.00206	0.01117	0.00259	0.03828
Unbalance	0.00215	0.01311	0.00388	0.01449	0.00241	0.02224	0.00205	0.02899

ABSD = Absolute Standard Deviation, RMSE = Root Mean Square Error

VIII. CONCLUSION

Artificial neural network has been found to be successful in predicting the coast down time for misalignment and unbalance in rotating machinery. In this research work, the radial basis network approach has been used for CDT data prediction as it employs limited neurons for the construction and requires lesser computational time in modeling the system.

The proposed technique of using radial basis function requires only limited experimental data points to train, model and predict the system behavior. RBF network was successfully implemented to predict CDT data for various mechanical faults. The performance of the RBF network in predicting the CDT is found to be more accurate. The work may be extended to classify the mechanical faults in rotating machinery. The same methodology can well be extended to condition monitoring systems as well as in analyzing vibration data in rotating systems.

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APPENDIX - A

SPECIFICATIONS FOR FORWARD CURVED CENTRIFUGAL BLOWER

Outer diameter: 135 mm
Inner diameter: 110 mm
Number of blades: 36
Chord length: 25 mm
Blade width: 71 mm
Blade thickness: 1.3 mm
Blade inlet angle: 112^0
Blade outlet angle: 129^0
Blade channel width: 10.20 mm
Diameter ratio: 0.815
Blower end exit duct area: 0.00295 m^2
Weight of blower: 2 kg

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BIOGRAPHIES

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