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Use of Radial Basis Function Neural Networks for Analysis of Unbalance in Rotating Machinery

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Abstract*— Rotor unbalance is the most common cause of vibration in any rotating machinery. The Coast Down Time is used as a condition monitoring parameter to monitor the rotating machinery. The CDT is the total time taken by the system to dissipate the momentum acquired during sustained operation, which is an indicator of mechanical faults. Experiments were carried out on Forward Curved Centrifugal Blower to record the CDTs at selected blower shaft cut-off speeds of 1000 rpm, 1500 rpm, 2000 rpm and 2500 rpm respectively for various unbalance conditions. These experimental CDT data were used to train the neural network. The paper also discusses the successful incorporation of radial basis function neural network (RBF-NN) for the CDTs prediction for unbalance fault conditions. The results showed that the RBFNN predicted CDT values are very close to the experimental CDT values.

***Index Terms*— Coast down time, Radial basis function neural network, Rotating machinery, Unbalance.**

I. INTRODUCTION

Rotor unbalance is one of the most common causes of vibration in any rotating machinery. 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. The force in rotor system is most often rotating unbalance, which can change due to the erosion or loss of material or accumulation of foreign material on rotating parts. The unbalance part of the rotor rotates at the same speed as the rotor and therefore the force caused by the unbalance is synchronous [1]. Mechanical damage and contaminant buildup are the two main causes of unbalance in fans. Unbalance in impeller is due to mechanical damage and corrosion.

Condition monitoring involves detection, diagnosis and prognosis of all rotating machinery components for their malfunctions such as rotor unbalance and misalignments, fractures, and contaminations etc., which would result in loss of production and also unwanted breakdown. Various condition monitoring techniques were exploring by many researchers, Coast Down Phenomenon (CDP) during deceleration period in particularly has attracted enormous attention. 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 behavior of the system during this period is known as the Coast Down Phenomenon. The exact time period between the power cutoff time and the time at which the rotor stops is called Coast Down Time [2]. CDT is the total time taken by the system to dissipate the momentum acquired during sustained operation. Extensive experiments were conducted on rotor system to evaluate the journal bearing lubrication [3] for different operating conditions and the influence of the rotor unbalance response [4] 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.

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 [5], [6]. The multi-layer feed forward back-propagation techniques were used to detect bearing faults [7]. Radial basis function neural networks require lesser neurons than the standard feed forward back-propagation networks [8]-[10]. They can be trained in a fraction of time. RBFNN is used to model engineering systems and found that it is efficient, reliable and robust technique [11].

The Coast Down Time analysis can be used as one of the condition monitoring parameter to assess the condition of the rotating machinery [12]. From the survey of literature, the application of RBFNN not extended to CDT prediction. The main objective of this paper is to develop neural network model that will be able to predict the CDTs for unbalance fault conditions.

II. RADIAL BASIS FUNCTION NEURON MODEL

A Radial Basis Function (RBF) 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 [13].

The general model of RBF neuron is shown in Fig. 1. 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.

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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.

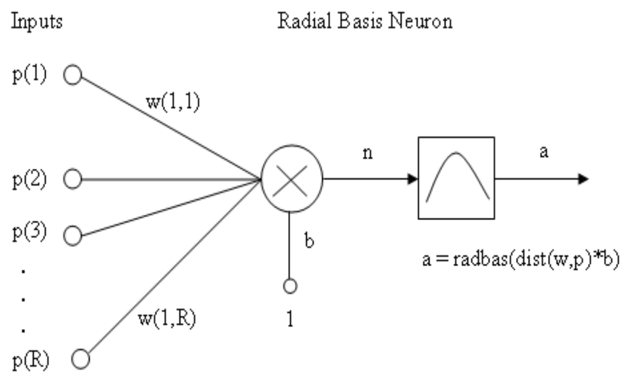

Fig. 1. Radial Basis Neuron Model

RBFN network is capable of approximating any arbitrary mapping. The main difference between the RBFN network and the back-propagation 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 back-propagation network in the case when the problem is extended to higher dimensions [14].

III. RBFNN TRAINING PROCEDURE

The radial basis function neural networks have been designed by using the function newrb in the neural network toolbox supported by MATLAB [15]. 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 function neuron. During the training, each of the connecting weights 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.

IV. EXPERIMENTAL TEST SETUP AND PROCEDURE

The photographic view of the Forward Curved Centrifugal Blower experimental test setup [16] used for this investigation is shown in Fig. 2. A Forward Curved (FC) centrifugal blower is mounted on a shaft with length 315 mm and diameter of 20 mm at the center position of 190 mm between two anti-friction bearings. The blower shaft is connected through an electromagnetic coupling to a variable speed DC motor. Two inductive proximity sensors are used to measure the speeds of blower and motor independently.

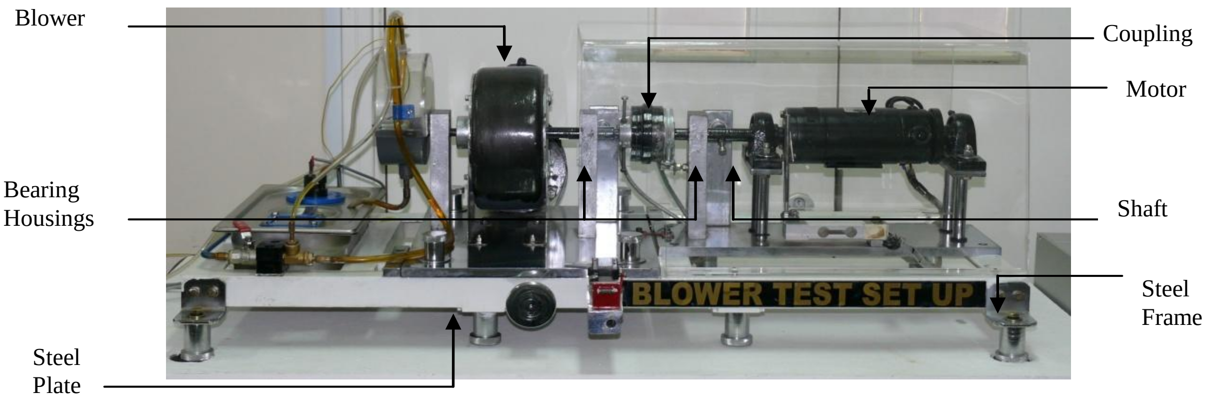

Fig. 2. Photographic view of Centrifugal Blower Test Setup

An instrumentation control panel is built-in to display and control the variables. The Visual Basic based application software developed along with instrumentation is used to control the operation of experimental test setup and to record motor and blower speeds as well as coast down time for each test run for selected cut-off 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 test, the power supply is restored for both motor and coupling such that they run continuously. The software used has the ability to record CDT with an accuracy of 0.06 seconds (60 ms) intervals and corresponding deceleration speed of blower and motor at each test run is saved in a data file.

The experimental tests at different cut-off blower speeds i.e., 1000 rpm, 1500 rpm, 2000 rpm, and 2500 rpm respectively have been carried out to record coast down time for different unbalance conditions. The masses have been added on blower impeller blade to create unbalance and to understand the influence of unbalance on CDT. Tests were conducted for three cases of unbalance condition by introducing additional mass of 20 gram-mm, 30 gram-mm and 40 gram-mm respectively at a radial distance of 61mm from the centre of the impeller blade. All the experiments were conducted by changing the mass in the same location in the impeller blade. The maximum unbalance weight added is restricted to 40 gram-mm as per the design specifications of the manufacturer. The coast down time and the respective deceleration speeds of blower shaft were recorded. These experimental data were used to train an ANN to predict the CDTs for various unbalance fault conditions.

V. RESULTS AND DISCUSSIONS

The CDTs and deceleration speeds are used to train and test the neuron to predict the CDT for different unbalance conditions. The input parameters were normalized before being applied to train and test the networks. Normalized CDT values range from 0 to 1. Normalized speed reduction values range from 1 to 0.

The RBF network was trained for the various unbalance conditions. From 27 CDT data points at various unbalance, 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. The trained network was used to predict the CDT data at different cut-off speeds, for aligned and balanced condition, and the results were compared with the experimental values as shown in Fig. 3.

The trained network was used to predict the CDT data at different cut-off speeds, for 20 gram-mm unbalance conditions, and the results were compared with the experimental values as shown in Fig. 4.

The trained network was used to predict the CDT data at different cut-off speeds, for 30 gram-mm unbalance conditions, and the results were compared with the experimental values as shown in Fig. 5.

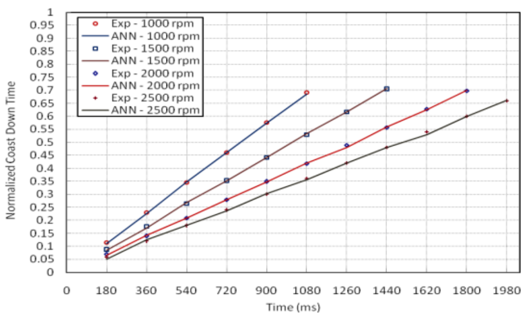

Figure 3: Experimental and Radial Basis Neural Networks Predicted CDT data at different blower shaft cut-off speeds for Aligned and Balanced condition.

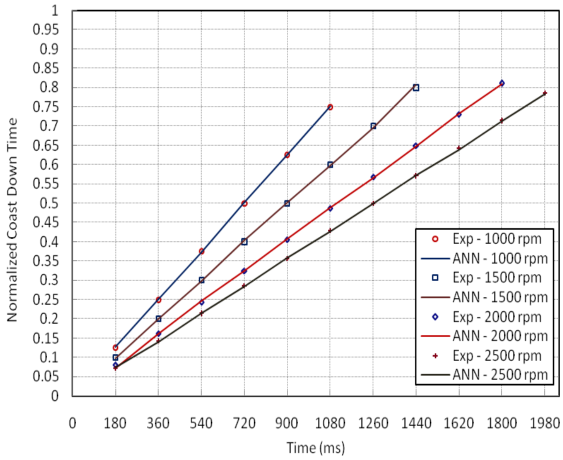

Figure 4: Experimental and Radial Basis Neural Networks predicted CDT data at different blower shaft cut-off speeds for 20 gram-mm unbalanced condition.

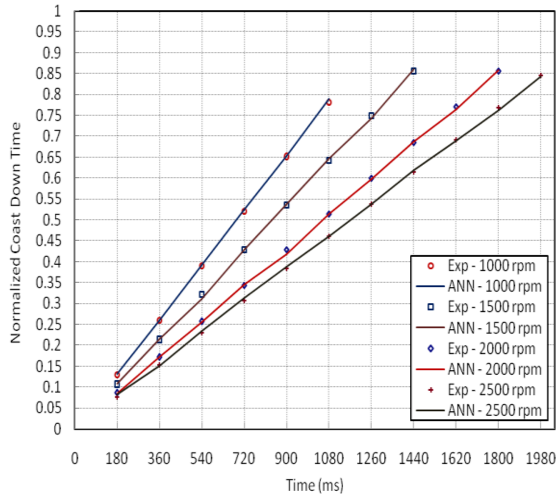

Figure 5: Experimental and Radial Basis Neural Networks predicted CDT data at different blower shaft cut-off speeds for 30 gram-mm unbalanced condition.

The trained network was used to predict the CDT data at different cut-off speeds, for 40 gram-mm unbalance conditions, and the results were compared with the experimental values as shown in Fig. 6.

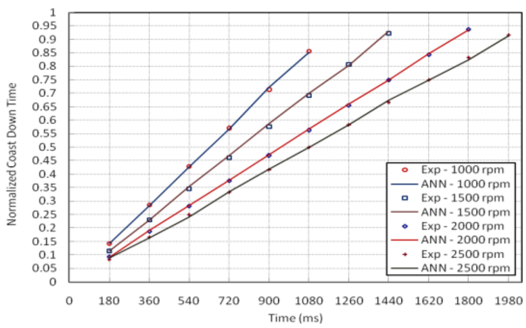

Figure 6: Experimental and Radial Basis Neural Networks Predicted CDT data at different blower shaft cut-off speeds for 40 gram-mm unbalanced condition.

The neural network predicted data were compared with the experimental values.

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It has been observed that Radial Basis Function neural network modeling of system based parameters is found to match closely with the experimental data at balanced and at various unbalance conditions. From the modeling, the results show that the distribution of experimental values and Radial Basis Function neural network predicted values are very close to each other. The absolute standard deviation and root mean square error calculated for various unbalance conditions at different blower shaft cut-off speeds are tabulated in Table. 1. The absolute standard deviation and root mean square error values are well within the permissible limits.

VI. CONCLUSION

In this paper, the radial basis neural network approach has been used for CDTs prediction for various unbalance fault conditions. The proposed technique of using radial basis function requires only limited experimental data points to train, model and predict the system behavior. RBFN network was successfully implemented to predict CDTs for various unbalance conditions. The performance of the RBFN network in predicting the CDTs is found to be more accurate. The RBFN based prediction of CDTs for mechanical fault in rotating machinery has been found efficient and reliable. This work leads to a new dimension of using RBFN as an effective tool to predict condition monitoring parameter. The modeling of RBFN to predict CDT is highly justified for the CDT as one of the diagnostic parameter to assess the condition of the rotating machinery.

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TABLE I
COMPARISON BETWEEN EXPERIMENTAL AND RADIAL BASIS FUNCTION NEURAL NETWORKS PREDICTED CDT VALUES FOR UNBALANCE

Mechanical fault	Blower Shaft Cut-off Speeds (rpm)							
	1000 rpm		1500 rpm		2000 rpm		2500 rpm	
	ABSD	RMSE	ABSD	RMSE	ABSD	RMSE	ABSD	RMSE
Unbalance	0.00315	0.01205	0.00315	0.01318	0.00252	0.02271	0.00245	0.02464

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