Investigation of Machine faults using Elman Neural Network and Decision tree

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Abstract. This paper demonstrates the application of an expert system aiming the diagnosis of rotating machineries to recognize and analyze the sources of abnormal vibration. A tailor made test rig is fabricated for the purpose of experimental investigation, and it is validated with the vibration severity chart. This paper discusses the approaches of the Elman neural network and Decision tree in the investigation of the predominant faults in rotating machineries. The various characteristics and operating conditions are determined. Using the neural network optimum results is achieved when the number of hidden neurons, learning rate and the momentum factor are 5, 0.1 and 0.9 respectively. In a decision tree, classification of faults is performed with the help of a cause-symptom matrix using the classification and regression trees algorithm. The functioning of the network and decision tree in diagnosing the rotating machinery was investigated based on the accuracy and convergence. The occurrence of faults such as unbalance, misalignment, bearing defects and looseness are predetermined. Expert system provides the information at right time when the operator is unavailable. The performance of the two approaches are compared and presented.

Keywords: Machine faults, Expert systems, Decision Tree, Elman Neural Network

1 Introduction

Determining the location and classifying the fault along with its monitoring is done in the control engineering for the investigation of machine fault. Status of the rotating machinery is diagnosed based on the information collected. It is essential to know about the knowledge of the system during the process of diagnosis. It was a hectic task for operator to predict the failures at the right time along with monitoring the health of a machine. When a machine is running continuously, failure of machine can be noticed which causes downtime of a machine. Breakdown maintenance was an expensive one, which greatly affects the production, where the machine runs continuously until the occurrence of failure. During the process of periodic preventive maintenance, machines are dis-assembled, overhauled and renovated thereby extending their useful life. Among the

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available predictive maintenance techniques, condition monitoring was universally used due to its compensation in the industries. The process of monitoring the machine condition called as condition monitoring. Classification of faults is of utmost importance in the condition monitoring of rotating systems using vibration analysis, used for the interpretation of the individual frequencies present in the signal due to the fault in the components. The analyst can identify the position and nature of problem, and sometimes even at the root cause also.

Different techniques have been developed to automate the condition-based maintenance procedure for various machineries [1]. Predicting the vibration spectrum of the rotor dynamic equipment for shaft misalignment has been performed through the experiment [2]. Captured frequency spectrum is validated with the help of numerical frequency spectra. A correlation between the fault and its symptoms was established to assist machinery diagnosis [3 & 4]. The dynamic response was studied to investigate the parallel misalignment of Jeffcott rotors with rigid type couplings [5]. Vibration response have been computed theoretically and validated experimentally for the rotor flexible coupling [6]. Predominant harmonics have been determined to be 2X of the running frequency. The magnitude of acceleration increases as the harmonics gets closer to the natural frequency. Change in harmonics is found as a result of the increase in misalignment. The effects of parallel misalignment with ball bearing system by vibration analysis have been discussed [7]. Experimental and numerical spectra were obtained for different combinations of misalignment conditions using the fabricated test rig [8]. Stability of rotors connected through mechanical coupling due to angular misalignment and its effects have been detailed based on the frequency analysis [9]. Developed a comprehensive approach to differentiate the faults utilizing the harmonic component and validated experimentally on different test-rigs and real machines [10]. Using the experimental dynamic set-up vibration due to friction and self-sustained caused by unbalance was explained using the experimental dynamic set-up [11]. The allowable amount of the unbalance and misalignment was explained and their remedies were suggested [12, 13].

Investigation was conducted for comparing the performance of the bearing fault diagnosis utilizing the artificial neural networks and its relative effectiveness was detailed [9, 14] with the help of feed forward neural network [15]. Detecting and diagnosing the faults present in the rotating machinery was performed by feed forward neural network utilizing the nonlinear neurons [16]. Signals from an non-defective and defective bearings subjected to loads and different speed conditions were captured and processed further in the neural network [17] and the success rate was assessed and related with other networks. The need of neural networks and their application were extended to the monitoring of bearings [18] and dynamic behavior of rotating systems [19]. The results of the experiment confirmed the possibility of utilizing the network for analysis of such systems. Development of a neural network was simulated with the help of the back propagation learning algorithm for predicting the fault present in the rotating machinery was illustrated [20, 21 and 22], using Adaptive Resonance Theory (ART) and the training by Kohonen neural network (KNN) [23], Elman Neural Network (ENN) [24]. The updated review of existing methods for creating the decision tree classifiers in a top-down manner was presented in an algorithmic framework [25]. Diagnosing the rotating machinery with the help of decision tree was explained efficiently [26]. The causes of abnormal vibration in rotating machinery are diagnosed using an expert system [27]. Diagnosing of the faults due to the presence of rotors is performed using the vibration-based machine learning (VML) approach with the parameters from the time domain and frequency domain [37]. When the rotor-bearing system is in a faulty condition, various step was taken to identify the exact type of fault [38]. The predominant fault in a rotor-bearing system viz, unbalances, misalignments, bearing defects and looseness have been identified. This paper deals with acquisition, analysis, evaluation of the vibration signals induced in the rotor-bearing test rig arising from various faults using the Elman neural network and Decision tree. The following sections of this paper highlight the experimental procedure, spectrum analysis, simulation of neural network and decision tree.

2 Experimental setup

The experimental setup comprising the following components ((i) an AC motor, (ii) a self-designed coupling (iii) a single-disk rotor) as shown in the Figure.1. Rotor shaft of 12 mm diameter and 700 mm length is held up by the two pillow radial bearings of span of 500 mm. The rotor shaft holds a disk of weight 887 grams of outer diameter 50 mm, is mounted on the mid-way of the supports [28] fastened by the radial screws. The bearing pedestals and motor supports are fastened to a steel base plate. Four symmetrical holes threaded at a radius of 35 mm to provide the desired amount of unbalance mass.

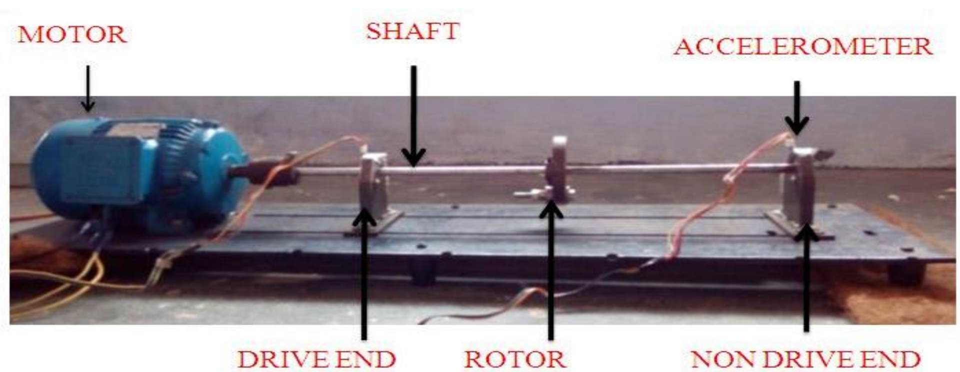

Fig.1. Experimental set up

2.1 Instrumentation used

An accelerometer (Range of ±5 V, dynamic range of over 100 dB and data ranging from 2 to 50 kHz) is used. Data rates on the input channel range from 2 to 50 kHz, with a sensitivity of 0.9 g.

Speed of the motor is measured with the help of a tachometer. Time domain and frequency domain are used for analyzing the extracted signals.

2.2 Conduct of experiment

Condition monitoring system to monitor the signatures arising due to a fault was developed with the help of a LABVIEW software. Placement of the sensor plays a vital role for detecting the impulse due to the defect. Hence, the accelerometer is placed on the bearing housing vertically to capture the spectrum at the bearing locations for single and multiple faults. The investigation was conducted to evaluate the condition of the machine running at the different speeds (500 rpm, 1000 rpm, 1500 rpm, 2000rpm) [29]. Diagnostics was carried out with the captured signals to predict the occurrence of the defects and their duration.

2.3 Experimental Analysis

Test rig is fabricated with utmost care to achieve a perfect balancing in the offline. Base data is captured from the test rig across the bearing locations to ensure that shaft are in perfect aligned condition. The effects of faults are investigated using the test rig after the introduction of faults artificially. The variation of the spectrum is observed after the introduction of faults as mentioned in the Figure.2 (a, b, c, d).

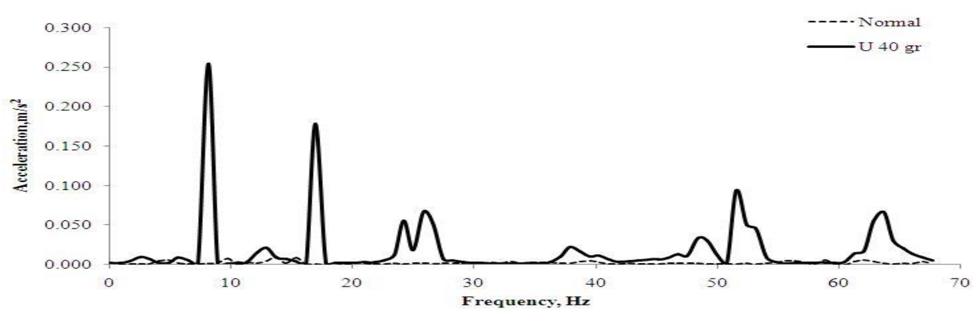

Fig.2(a). Spectrum of Unbalance(40g) at 500 rpm

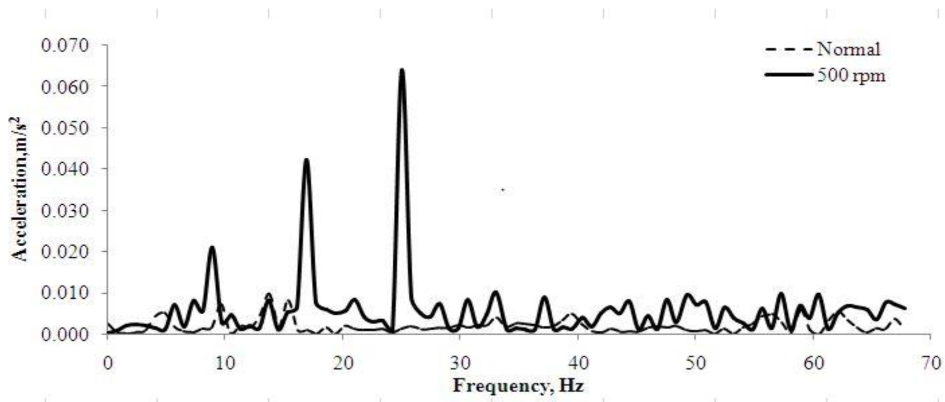

Fig.2(b). Spectrum of Misalignment 1mm at 500rpm

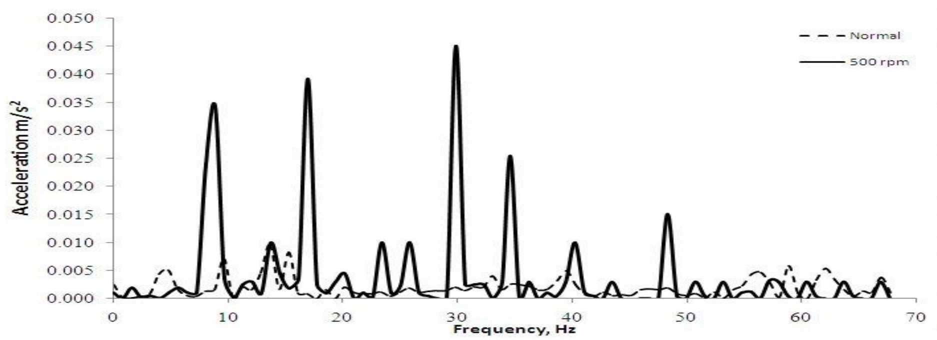

Fig.2(c). Bearings defects at 500rpm

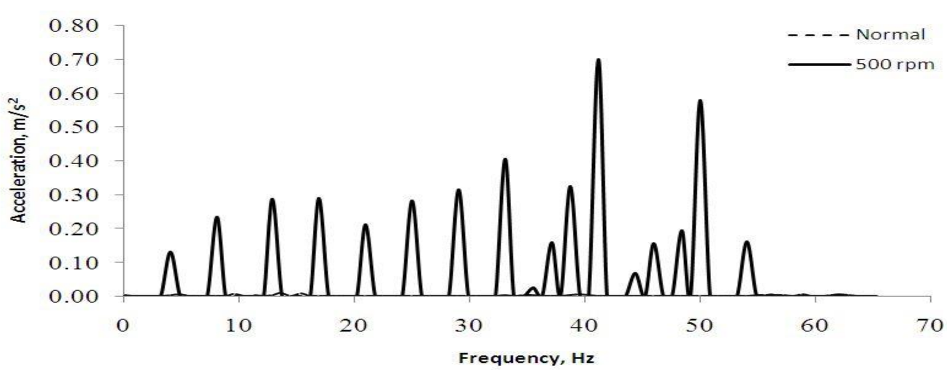

Fig.2(d). Looseness at 500rpm

For each faults, amplitude of the vibrations is captured and it is plotted where the horizontal axis is considered as frequency and acceleration on the vertical scale. Spectrum due to vibration is noticed to have a relationship with speed. The spectrum of acceleration with rotor unbalance at the mid of the bearing supports for the speed of 500 rpm) is shown in Figure.2 (a). Dotted line in the spectrum illustrates the normal condition, while the normal line shows the spectrum due to unbalance of 40 grams. The maximum magnitude of acceleration occurs at 8 Hz (1X) of the operating frequency with a maximum value of 0.250 m/s2. As the degree or extent of unbalance is varied the maximum magnitude increases in comparison to the previous condition. Due to the presence of unbalance, 1X component of the spectrum shows the predominant one. From the Figure.2(b), predominance is observed at the harmonics (1X, 2X, 3X) of the operating frequency of the test rig due to misalignment. Predominant peaks of 1X, 2X, 3X and the subharmonics in the spectrum are identified in the Figure.2(c) which illustrates the presence of bearing faults. Figure.2(d) illustrates the multiple harmonics of the operating frequency in comparison with the normal condition due to the looseness fault.

3 Elman neural network

A recurrent network [30 -33] comprising context layer possessing context units and hidden layer are shown in Figure.3. Elman neural network [34] trained, supervised, uses the error back propagation algorithm, which updates the weights of each layer to decrease the dissimilarity between the output and the desired output.

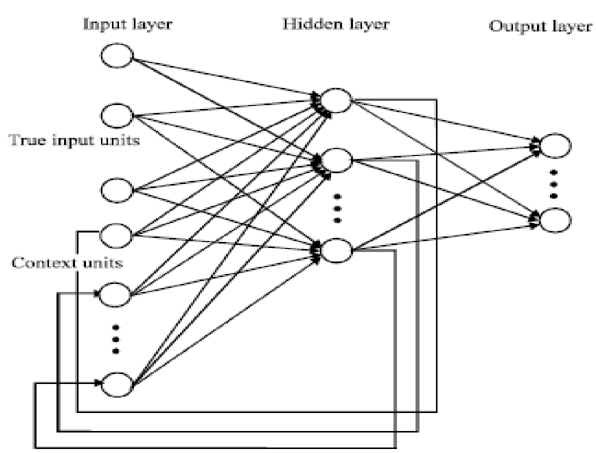

Fig.3. ELMAN network

3.1 Input parameters for NN

Network is modeled and simulated in the MATLAB, and its parameters are tabulated in the Table.1. Modeling of the network is accomplished by assuming as a two-class problem. Network is trained and tested to provide the information of the presence of fault. Data's of the captured signal is fed as input to the network. Among the datasets, 60%, 20%, 20% of data's were used for training, testing and validation of the network respectively. Simulation of the network is performed for the learning rates of 0.1, 0.2 &0.3. When the error is of high value and learning rate is of 0.2, result does not converge. When the learning rate is of high value large number of oscillations occurs. To arrest the oscillations, momentum factor is considered in the network. Based on different trials learning rate and momentum factor are considered as 0.1 and 0.9 respectively. Diagnosis performance depends on the number of hidden layer neurons in the network. If the number of neurons is of high value, rate of convergence decreases and the number of epochs increases. If the number of neurons is of low value, desired accuracy is not achieved. For the purpose of simulation in this research input neurons is set as 1, whereas the hidden neurons lies in the range of (3, 5, 7, 9, 11, 13 & 15). Simulation of the neural network is simulated on the basis of above discussed factors.

Table 1. Network output

No of Hidden Neurons	**3**		**5**		**7**		**9**		**11**	
	Actual Classes									
Predicted Classes	**0**	**1**	**0**	**1**	**0**	**1**	**0**	**1**	**0**	**1**
0	0	0	0	29	0	10	0	4	0	43
1	28	996	30	965	28	986	26	934	28	952
Precision	0	0.97	0	0.97	0	0.97	0	0.97	0	0.97
Sensitivity	0	1	0	0.97	0	0.99	0	1	0	0.96
Specificity	1	0	0.97	0	0.99	0	1	0	0.96	0
Mean Square Error	0.093785		0.0471		0.047911		0.061533		0.093644	
Accuracy	0.97		0.97		0.96		0.97		0.93	
Epochs	991		996		998		999		1000	

3.2 Network Results

Experiments were conducted for (16, 4, and 4) combinations for training, testing and validating the network respectively using MATLAB with the available data. The developed NN model comprises 1 input neuron, 3/5/7/9/11 hidden neurons and 1 output neuron with the TAN Sigmoid as activation function. The convergence for the optimized network occurs when the hidden neurons is 5 for the network are shown in Figure 4.

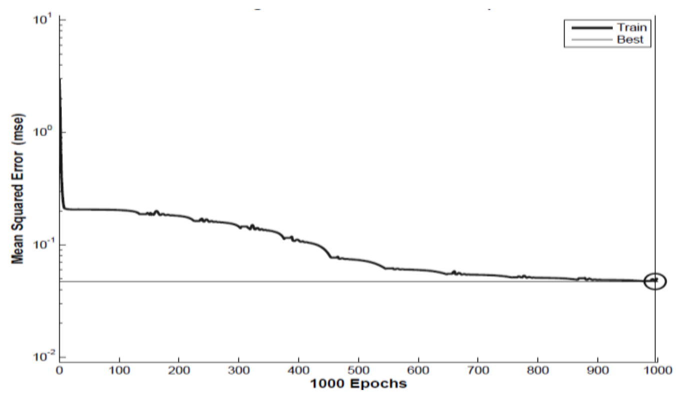

Fig.4. Training Curves for NH-5,996 epochs

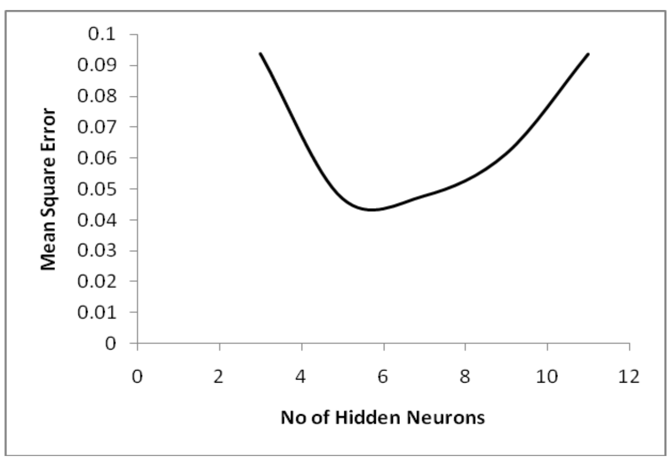

Fig.5. Performance curve of network model

The performance for each hidden layer is determined and tabulated in the last three rows of Table 1. The accuracy of 97% is achieved for the network with 5 hidden neurons with 0.0471 MSE at 996 epochs. When the hidden neuron is increased to 7, accuracy of 96.6% was obtained at 998 epochs with the same MSE value. Though the similar results of the network have been produced for the hidden neurons of 5 & 7, but the training time for 7 is greater than 5. Hence the network with 5 hidden neurons, 0.1 as learning rate and 0.9 as momentum factor is an optimized one for the fault detection. The performance of the neural network is shown in Figure 5 based on the mean square error for each hidden neurons.

4 Decision Tree

Information from the signal are represented as features in the tree format is called as Decision tree. To analysis the abnormal vibration on probability basis decision table relating the cause-symptom matrix is utilized. A Structured knowledge for the development of vibration expert systems was constructed using the decision table and decision tree.

4.1 Construction of Decision Tree

An expert system is constructed on the basis of association between the symptoms and fault gathered from an empirical knowledge through direct experience with the system [35]. The rules of the decision tree consist of disjunctions of conjunctions, which are paths from the root node leading to the leaf nodes. Classification of one instance is done by tracing the corresponding path for that instance, from the root node till it ends to a leaf node. The extracted signals are diagnosed using the decision tree and table with the guidance of cause- effect relationships. The decision tree depends on the attributes and class of the problem, based on the attributes, various IF then Else questions is raised to the data’s, which classifies the set of data’s [36]. According to well defined conditions, all inputs get passed to the designated coding. Then each data is assigned to its own class in the classification. Each value is recorded during the classification. The numbers of individual classes, total number of classes, their respective frequency, details of amplitude values are detailed. They can be used for the construction of the Decision tree. The classes are formed in this research for investigation of faults in rotating machinery. The various classes (cause of vibration) are classified on the basis of experience and its details are given in Table 2. With respect to the cause of vibration the attributes are listed in the Table 3.

A decision tree is formulated after the repeated diagnosis based on the cause-symptom matrix, which is used for examining the unwanted vibration. Decision tree is also used for analyzing the unwanted vibration. Decision tree is also used along with the decision table to realize the structure of knowledge, which is needed one to develop the needed vibration expert systems (VEXPS). Investigation of the machine faults (Unbalance, Shaft Misalignment, Bearing faults) are carried out in this paper. Using the decision tree and table faults are classified with the help of cause-symptom matrix. Faults are diagnosed for the spectrum signal captured from the rotating machineries utilizing the expert systems and it is validated.

Table 2. Class of the DT

S.No	Class(Cause of vibration)	Symbol
1	Unbalance	U
2	Critical speed	CS
3	Partial rub	PR
4	Oil whip	OW
5	Ball bearing damage	BBD

Table 3. Attribute of the DT

S.No	Attribute
1	What is the predominant frequency?
2	Is there a natural frequency?
3	Is the 0.4-0.48X component predominant?
4	Is the 0.5-1X component predominant?
5	How is amplitude change during shutdown?
6	What is the predominant location of vibration?
7	Is bearing damage frequency predominant?

4.2 Simulation of decision tree

The required information for the decision tree is fed in a user-friendly manner. Entry of the details in a step by step manner can reduce the various logical error occurs during execution of program. In this paper, the execution of decision tree and table are performed using the CART algorithm, codes are developed using the MATLAB software. The code was written based on the class, attributes and frequency fault relationship matrix. All the required inputs regarding the machineries are read from the user. All the required variables are declared and initialized. With reference to the values of amplitudes, the code reads each line of the input value, and then comes to a conclusion to frame the prediction rules for the further diagnostics of unknown details of the machineries. The production rule is shown in the Table.4 for the faults like Unbalance and Misalignment. Rules comprise precondition and consequence sets. A precondition set consists of one or more prerequisites while a consequence set consists of the consequences. The rules of expert system are framed on the basis of the sequence in order.

Table 4. Production Rule

	Type of set	Rule
IF	Precondition	Amplitude of first harmonic (1X) is higher and Amplitude of second harmonic is lower and Amplitude increases with increase in operating speed or Amplitude decreases with decrease in operating speed.
Then	Consequence	Unbalance
Else	Consequence	Misalignment

Confusion matrix for the expert system is as shown in the Figure 6. The classification accuracy of the expert system is of 96 % for the data collected from the fabricated test rig.

		ACTUAL CLASSES				
		1	2	3	4	5
PREDICTED CLASSES	1	10	0	0	0	1
	2	0	10	0	0	0
	3	0	0	10	0	0
	4	0	0	0	9	0
	5	0	0	0	1	9

Fig.6. Confusion Matrix

5 Conclusion

A test rig with various combinations of defects was built and an experiment was performed. Based on the vibration severity chart guidelines, obtained results are validated. Excitation forces produced from a machine during the processes was determined by the vibration analysis. Produced forces depend on the condition, characteristics of the machines which are used to diagnose the problem. In this paper identification of the fault, using the ENN and DT was discussed and presented. Classification efficiency and effectiveness was based on the convergence and accuracy. Neural network classified the faults with 97% accuracy whereas decision tree was 96% of classification accuracy. Success of the diagnosing network depends on the neuron size in hidden layer, momentum and learning terms. The developed decision tree algorithm has been trained and tested using the laboratory data collected from a test rig. The development of the expert system through a decision tree has been designed to meet the requirements of dimensions of a rotating machineries system. Vibration problems arising from a rotating machinery can be diagnosed using the developed expert systems on the occasions of the absence of the experts.

Notes

1) No Funding was received
2) Compliance with ethical standards
3) Conflict of interest

The authors declare that they have no conflict of interest.

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