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Vibration Signature analysis of Centrifugal Pump through Pattern Recognition System

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***Abstract*— Shortcoming Detection in apparatus is carried out by standard condition observing and vibration examination. Programmed issue discovery strategies are dependable, quick and precise that can be connected to discover answers for various issues. Intelligent condition Monitoring System for flaw identification focused around dynamic Multilayer Feed Forward Neural Network is a computerized framework that recognizes blunders in hardware focused around prepared neural system model. The destination of the current examination is to acquaint a novel methodology with the vibration signature dissection of rotating machinery utilizing pattern recognition approach. This work utilizes the execution of Back propagation Neural Network in grouping the different hardware blames by utilizing the marks got from the vibration sensors. The system is powerfully created basing on the prerequisite of info and yield hubs and number of shrouded layers can be connected to various issues. The results are contrasted with manual estimations and found with be precise and dependable.**

Keywords—Condition Monitoring, Vibration Analysis, Signal analysis, Soft computing.

I. Introduction

Condition observing is paramount for securely drawing out the life of immoderate holdings [1]. Nonetheless, numerous condition observing frameworks create a lot of information for specialists to view and survey, prompting helpful pointers of wellbeing being disregarded. Upkeep of hardware supplies is done to expand the accessibility and unwavering quality, with the goal that it will keep on operating satisfactorily for the whole life-cycle of the gear with obliged expense viability [2]. This could be settled with a condition observing structural engineering fit for abnormality location, finding, and visualization, removing however much data as could reasonably be expected from condition information.

Condition monitoring involves determining the condition of a machine and its peak rate of change of measured parameters in order to determine the maintenance requirement and application. The condition of machine may be determined continuously or at regular class intervals by monitoring measurable parameters [3].This preventive maintenance application is for detecting all maintenance problems arising by wear and tear in rotating machinery. It is a unique resource for improving maintenance management processes and learning smart preventive maintenance (PM), condition monitoring, inspection and troubleshooting techniques on a wide variety of components include pumps, motors, gears, bearings, chain, pipes and valves, couplings, seals, fans, lubrications, lifting equipment, hydraulics, pneumatics, compressors, steam and electrical systems. The condition monitoring and PM techniques are particularly useful to inspect and prevent failures for a number of standard components [4]. The maintenance techniques allow setting up and improving a preventive maintenance program in any industry.

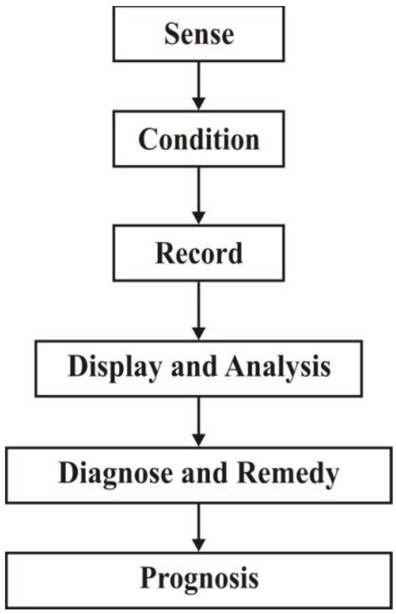

Fig. 1. Vibration Analysis Procedure.

II. Vibration Analysis

Excessive vibration in rotating machinery severely damages its parts like rotary elements, bearings, shafts etc. Periodical checking and vibration analysis are important aspects to avoid these vibrations. Vibration analysis is used primarily with rotating equipment to find problems such as out-of-balance, looseness, misalignment, gear teeth defects, bearing defects and system resonance [5, 6]. Generally periodic readings are taken and recorded. Maintenance personnel then compare these readings peak values to a baseline. When vibration reaches a certain level, then root cause of high vibration is analyzed and corrective action plan is prepared to reduce the amount of reactive maintenance and ensures that replacement occurs with minimum impact on the production or facility schedule. The vibration analysis procedure is as shown in Figure 1.

Step 1: The first step is to sense the vibration experienced by the structure with a help of transducer to measure the various parameters associated with vibration. Transducer is a device that coverts vibratory motion into an optical, mechanical or mostly commonly electrical signal proportional to the experienced vibration.

Step 2: In the condition module, the signal obtained from the transducer needs to be conditioned before recording. It can be achieved by filtering, where certain components of the signal are either eliminated or amplified. A pre-amplifier is generally used to condition the signal, which incorporates both, filter and integration circuits.

Step 3: In Record module, data is recorded on electronic data collector. They allow measurement of vibration at different peak points and periodic class intervals.

Step 4: In the Display and Analysis, the measured variables need to be viewed in desired form in order to analyze the data by performing spectral analysis.

Step 5: In Diagnose and Remedy, each machine defect produces a unique set of vibration components that can be used for identification. Various causes of Vibration considered are Unbalance, Misalignment, Bearing Problem, Mechanical Looseness, Resonance, and Gear Problems. Machinery dynamics, operation conditions, multiple faults and speed variations affects the vibration, thus complicating the correlation process. In order to rectify, fault has to be identified, and once the fault is identified, remedial action is taken up in the form of repair or replacement.

Step 6: Final step of vibration analysis is the prognosis where the remaining life of the machinery can be estimated.

III. BACK PROPAGATION NEURAL NETWORK

The back propagation algorithm looks for the minimum of the error function in weight space using the method of gradient descent. The combination of weights[7][8][9] which minimizes the error function is considered to be a solution of the learning problem. This method requires computation of the gradient of the error function at each iteration step that guarantees the continuity and differentiability of the error function [10].

One of the more popular activation functions for back propagation networks is the sigmoid; a real function is defined by the expression.

$$S_c(x) = 1/(1+e^{-cx}) \qquad (1)$$

The constant c can be selected arbitrarily and its reciprocal 1/c is called the temperature parameter in stochastic neural networks. The shape of the sigmoid changes according to the value of c, as can be seen in Figure 2. The graph shows the shape of the sigmoid for c = 1, c = 2 and c = 3.[11] Higher values of c bring the shape of the sigmoid closer to that of the step function and in the limit c ! 1 the sigmoid converges to a step function at the origin. In order to simplify all expressions derived in this chapter we set c = 1, but after going through this material the reader should be able to generalize all the expressions for a variable c. In the following we call the sigmoid s1(x) just s(x). [12]

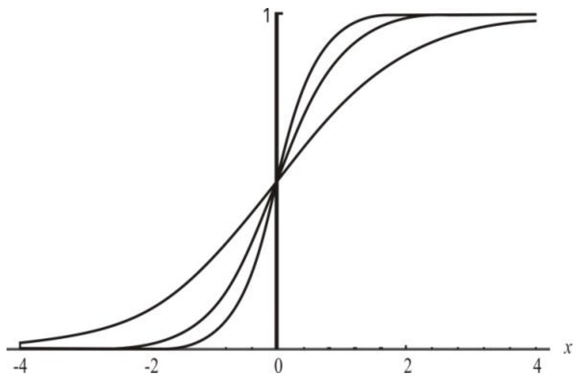

Fig. 2. Three sigmoid (for c = 1, c = 2 and c = 3) Network

The BPNN is stopped when the value of the error function has become sufficiently small. The BPNN can be decomposed in the following four steps:

- Feed-forward computation
- Back propagation to the output layer
- Back propagation to the hidden layer
- Weight updates

A. *Algorithm for the BPNN.*

The Algorithm for Back Propagation Neural Network [13][14] is as follows:

Step 1: Input training vector.
Step 2: Hidden nodes calculate their outputs.
Step 3: Output nodes calculate their outputs on the basis of
Step 2.
Step 4: Calculate the differences between the results of Step 3
and targets.
Step 5: Apply the first part of the training rule using the results
of Step 4.
Step 6: For each hidden node, n, calculate d(n).
Step 7: Apply the second part of the training rule using the
results of Step 6.
[Steps 1 through 3 are called the forward pass, and steps 4 through 7 are called the backward pass]

IV. CASE STUDY: CENTRIFUGAL PUMP

Centrifugal Pumps are used to move air in various industrial applications. Its heavy-duty construction and sophisticated design makes it durable and highly efficient. The pumps are used in diverse industries. The technician records vibration signatures at regular maintenance intervals and the signatures

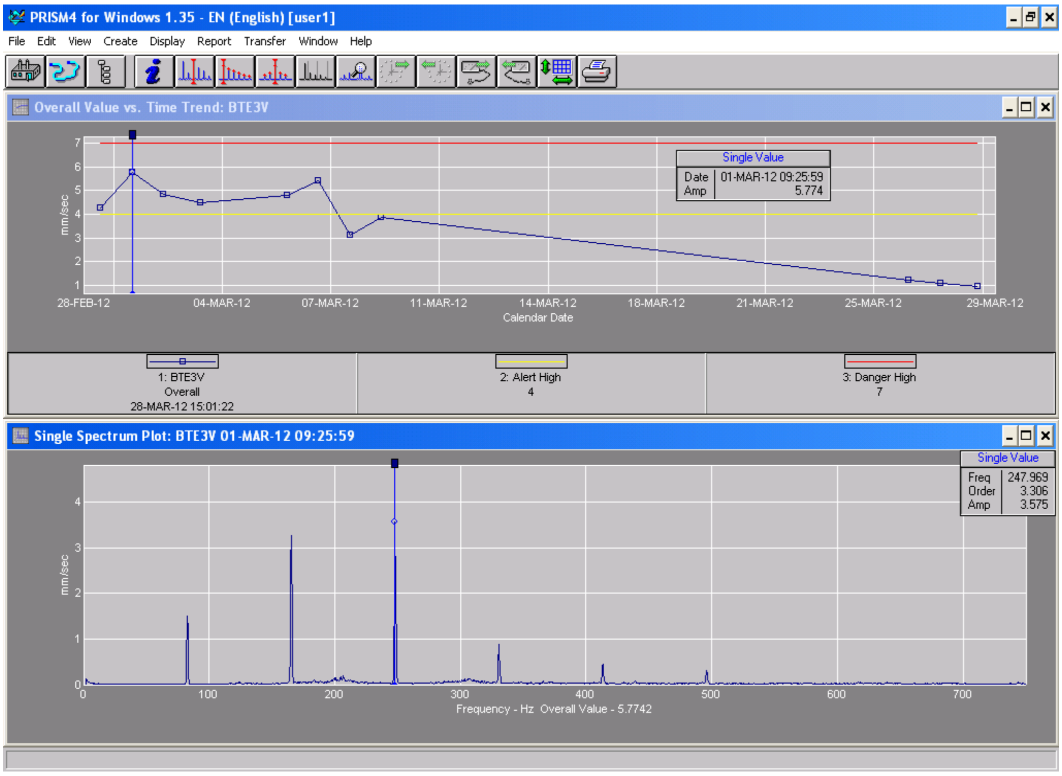

Fig. 3. Vibration signature at non-drive end

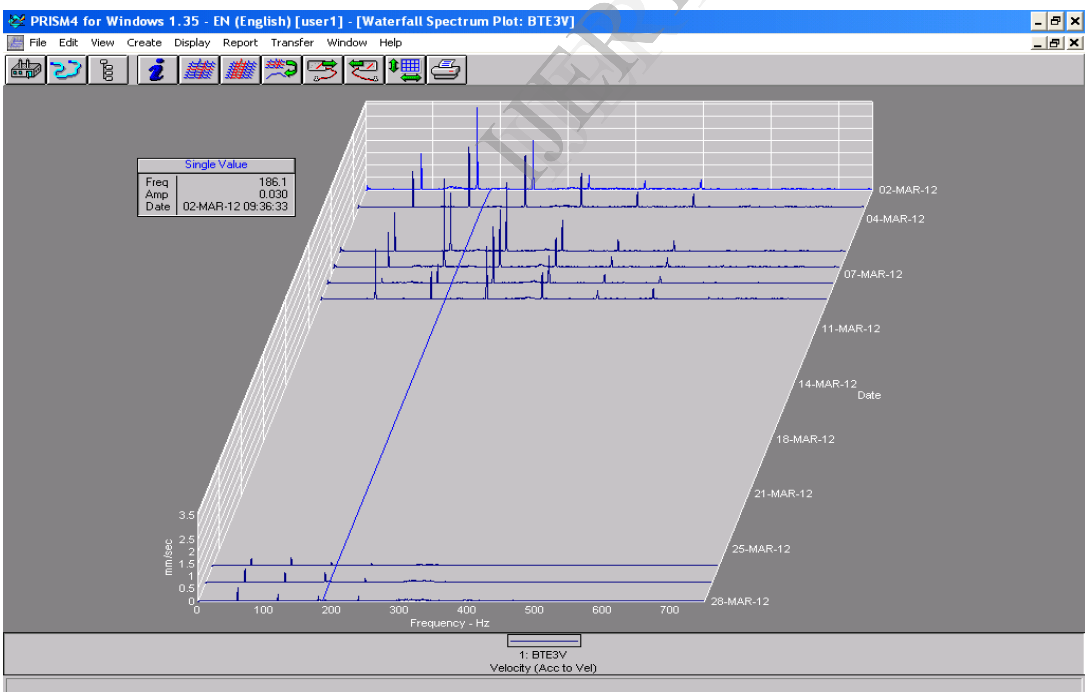

Fig. 4. Waterfall model for the Vibration signature at non-drive end

are compared with expectations associated with normal behavior and specific faults. The expectations are typically expressed in terms of dominant frequencies for specific sensor locations and types of equipment. Significant changes in the frequency content can indicate specific mechanical problems as shown in Figure 3 & 4.

Mathematical Analysis

The dominant frequency equation is as shown in equation 2.

$$(f) = (V * 19120) / D. \tag{2}$$

Where velocity measurement (V) in millimetres/sec, Displacement measurement (D) in micrometers, dominant frequency (f) in cycles per minute. The cause of vibration can be analyzed based on the ratio between dominant frequency and the speed of the Centrifugal Pumps as shown in Table 1.

Table 1. Fault Detection Analysis based on dominant Frequency.

Dominant Frequency in RPM	Most likely Trouble
1*Speed(N)	Unbalance
2*Speed(N)	Looseness or Misalignment
3*Speed(N)	Bearing Defects

V. ANALYSIS AND RESULTS

The system adapts Artificial Neural Network for the analysis of Vibrations generated by the Centrifugal Pump. The training set is given to the network which consists of three inputs namely Speed (N), Velocity (V), Displacement (D) and one output, which is the ratio between dominant frequency and the speed. The network is trained with one hidden layer with two neurons. Then the system is tested against new inputs and output is taken from the network. Figure 5 illustrates the process of the three layer neural network with three inputs and one output. Training the neural network has been done by using the dataset which is collected from industry.

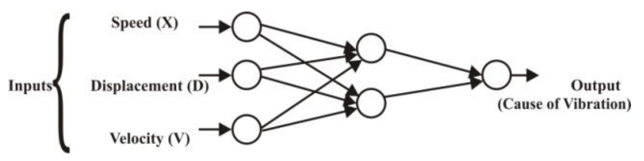

Fig. 5. Network used for case study.

A. *Correlation of Mathematical and ICM Analysis.*

The system is exclusively tested for different type of fault detection such as unbalance, misalignment and different types of bearing faults in the Centrifugal Pump. Data is collected periodically from one of the Centrifugal Pumps of LG polymers, Visakhapatnam. Table 2 gives the compared results of both mathematical analysis and ICM analysis.

Table 2. Fault Detection Analysis based on dominant Frequency.

Description	**Set 1**	**Set 2**	**Set 3**
Speed(N)	2200	1600	2100
Velocity(V)	2	5	7
Displacement(D)	8	5	3
Mathematical Analysis	Unbalance	Bearing Problem	Unbalance
ICM Analysis	Unbalance	Bearing Problem	Unbalance

The Artificial Neural Networks algorithms are coded in mat lab. The results are tested exclusively by the numerous samples collected from industry. The comparison analysis is done and the results are tabulated in Table3.

Table 3. Optimized values for Classification Accuracy

No of Hidden Neurons	Training Set	Classification Accuracy
		BPNN
1	2500	30
3	2500	34
5	2500	36
10	2500	45

Though the algorithms are applied to a single application based on pumps they can be extended to other rotating machinery where mathematical analysis is not reliable as it is error prone and time-consuming.

VI. CONCLUSION

This paper presents an approach of framing and designing Artificial Neural Networks based on Back Propagation algorithm. Though the code is tested on industry samples for Fault Detection in Centrifugal pumps, the concept with minor changes can be used for condition monitoring in other similar application.

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