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Application of Artificial Neural Network Models for Condition Monitoring of Industrial Fan

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Abstract: The condition-based maintenance philosophy receives a significant amount of attention during the operation of machine maintenance. It is an effective tool for lowering the cost of maintenance, decreasing the number of times machines are offline, and preventing unscheduled breakdowns of machines and equipments. This study aims to boost the plant's availability by safeguarding it against failure in its early stages and assuring the general safety of people and machinery. In artificial intelligence (AI), adaptive system technologies such as neural networks have been used successfully for monitoring the condition of machines. This paper aims to highlight the application of Artificial Neural Network (ANN) techniques or models in condition monitoring of industrial fans and blowers using vibration signals and, in turn, comparing the performance of the same for training and testing time, quantifying and classifying the faults. test success and accuracy.

Keywords: *Condition monitoring, Artificial Intelligence (AI), Artificial Neural Networks (ANN), Industrial Fans & Blowers*

1. Introduction

Machine condition monitoring and predictive maintenance have the same overarching aim: anticipate and locate any machine faults or problems before they manifest themselves. Condition monitoring and predictive maintenance both have similar goals: to reduce the number of times machines are offline, to reduce the machine shutdown time, to cut down on the amount of money spent on maintenance, and to improve the machine safety, reliability, and availability.

To achieve the aim of monitoring the condition of machine and fault detection with subsequent correction, artificial intelligence (AI) has been employed relatively effectively in some disciplines to tackle challenges connected to industry and organization. A computational expert system based on artificial neural networks (ANN) and fuzzy logic can be developed to automate the condition monitoring of various machines. This system can perform reliable fault detection and categorization using extracted features from monitoring parameters such as vibration, noise, and pressure pulsations.

In industrial plants, a wide range of fans serve various functions, and the fans themselves are regarded as important or vital critical machinery. The existence of defects such as imbalance, misalignment, mechanical looseness, resonance, aerodynamic forces, and so on will lead to an increase in vibration level and other parameters, which must be rectified quickly before failure occurs.

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This paper aims to show and explain AI-based ANN models that may be used effectively for condition monitoring and fault detection of such machines. These techniques can be applied to a variety of various devices and machines.

1.1 The need to do a machine fault diagnostic

Complexity is a hallmark of today's plant life. A decrease in productivity and increased operating costs are the direct results of malfunctioning process equipment and instrumentation. A defect that goes undetected or unchecked may cause the breakdown of connected equipment and, in the worst-case scenario, can lead to catastrophic failures or accidents. An early diagnosis of a machine problem may save significant money on unexpected maintenance and missed productivity costs.

1.2 Condition Monitoring of Machine

Monitoring the condition of machines or equipment is an essential component of diagnostic maintenance. State monitoring is the practice of monitoring the condition of a machine by utilizing certain quantifiable factors such as vibration, temperature, and noise, amongst others, to discover changes that might signal a growing malfunction. It is the process of monitoring certain characteristics of the equipment in question and keeping track of any major changes that may indicate an imminent breakdown.

Keeping an eye on items such as:

• Oil sampling and analysis (Spectrographic Oil Analysis Procedure, i.e., SOAP)

• Analyses of emitted gases,

• Measurements of vibrations,
• An examination of the noise,
• Thermography using infrared light and
• Methods of inspection that do not cause damage

First and foremost are procedures that are based on condition monitoring and provide an in-depth look at the present state of a machine.

1.3 Industrial Fans

In industrial settings, one can find number of different kinds of fans in use. They have the potential to be regarded as important or essential machines:

1. Centrifugal Fans
2. Axial Fan

1.4 The fans most often cause the following issues:

1. Unbalance
2. Misalignment, Parallel and angular
3. Loss of mechanical precision and structural fragility
4. Bent shaft, Eccentric rotor, and bent rotor
5. The presence of aerodynamic forces, among other things, resonance.

As they are critical machines, the problems must be addressed before they stop working properly.


Fig 1: Cooling Fan

2. Literature Review

Results from applying the study are discussed here, with visual representations of those findings provided via waveform and spectrogram in both the X and Y axes. Mostafa Metwally [6] and team partners presented their findings as a comprehensive investigation of vibration analysis for machine monitoring and diagnostics using AI/NN methods and models. Following FFT analysis, the data are sent into an artificial neural network, where they are utilized to determine whether or not the machine is working normally. To some extent, preparing the input data may boost the efficiency of ANNs and ANFIS models. A. The frequency and time-domain plot of the recorded vibration signal from the data acquisition (DAQ) system gives a graphic illustration of the vibration signal in the frequency and time domain. The present study also provides exposure to a trend graph for typical monitoring, alarm levels and frequency spectra for a faulty condition and an average spectrum.

In their study, B. Kishore et al. explored an intelligent Condition Monitoring approach using Artificial Neural Networks (ANN) in combination with Genetic Algorithm (GA), focusing on air blowers. They proposed that with slight modifications, this concept could be extended to monitor the condition of other applications as well. The research paper presents the development and comparison of two ANN models: one based on the Back Propagation algorithm and the other on the Radial Basis Function. Both models were optimized using a genetic algorithm [5].

Rolling element bearings in induction motors are the focus of Omar Alshoerman and coworker's review of artificial intelligence systems for condition monitoring and fault diagnosis. The article describes many AI approaches, some of which use neural networks, and emphasizes their applicability to industrial machinery, automation, and processes [7].

Cory W.T.W. has outlined the methods for condition monitoring, including the fundamental equation of vibration and the perturbing forces involved. Baseline signature and other methods for predicting problems when industrial fans will start failing are also examined [8].

The authors of this article, Mohamad Hazwan et al., provide an in-depth study of current developments in vibration analysis to monitor and diagnose machines. Data is collected using analyzers and sensors; characteristics are extracted, and (AI) artificial intelligence-based algorithms are applied for fault diagnosis [9].

The study also included a Frequency Domain Analysis. The amplitude is plotted against frequency in a frequency domain study, and the findings are compared to those produced in a time domain analysis. It is easier to discover resonant frequency components utilizing frequency domain approaches, one of the many ways these methods aid in the machine's fault diagnosis process. It is only via an analysis of the signal in the frequency domain that several signal features may be detected that are otherwise invisible from a time domain perspective.

Time-frequency based analysis considers both the time domain and the frequency domain analysis. It suggests that this method may simultaneously discover the signal's frequency component and its time-variant qualities.

Artificial neural network (ANN) based techniques are widely recognized as one of the most reliable techniques for condition monitoring of rotating equipment like industrial fans. The "neurons" in a NN are a lot of artificially created neurons called "nodes," and they are all very closely connected. A network is built up of these individual nodes linked together in stages. Processing raw vibration data collected with the frequency above and time-frequency domain techniques, NN can simulate processes and systems. In the course of NN's training process, more significant variables may be cancelled out by others that are less significant. The data must go through the proper processing and scaling procedures before entering the NN. Raw data on vibration may be simplified to reduce the input variable's impact if normalized to a range between 0 and 1. If the training time increases linearly with the network's complexity, then the accuracy of the results will suffer accordingly. In machine diagnosis, the backpropagation neural network (BPNN) is widely used because of its robustness and efficiency in dealing with noisy data.

Aroui T. et al., promoted the use of a rotor-mounted feed-forward neural network in induction motors. A fault detection system was developed utilizing feed-forward neural networks to identify, categorize, and evaluate the severity of rotor flaws in induction motors by monitoring the stator current [10].

Samanta B. and their team conducted a comparative study to assess the performance of three different neural network models in identifying bearing defects: the multilayer perceptron (MLP) model, the radial basis function (RBF) network, and the probabilistic neural network (PNN) [11].

In a separate study, Purnawansyah B.N evaluated the accuracy of both RBF and backpropagation neural network models for predicting daily network traffic [12].

Additionally, Vana Vital Rao and their partner explored the use of vibrational analysis as a diagnostic tool for monitoring critical bearings. They trained an artificial neural network (ANN) using datasets obtained from a series of test runs to predict the size of defects in a specific bearing relative to the vibration root mean square (RMS) velocity [13].

Labib Sharrar et al.compared the various techniques of vibration analysis for an industrial cooling fan in mentioned article.The fault diagnosis techniques explained in the study, which include image encoding and CNN and fuggy logic and underlined that with this type of intelligent monitoring system, companies could avoid downtime and costly repairs and ensures the overall safety of man and machines [14].

Utilizing vibration signal analysis in conjunction with artificial neural networks (ANN), Said Haggag and his colleagues described a method that is efficient and trustworthy for locating and diagnosing defects in a centrifugal type ETRR-2 research reactor core coolant pump [15]. This method was developed utilizing artificial neural networks. The amplitudes and frequency domain data of vibrations are taken as input by the ANN model, which has the capability of identifying a variety of difficulties including bearing flaws, misalignment, the degree to which the imbalance is present, and mechanical looseness.

After the first stage of parameter elaboration is complete, the next step is to carry out a Levenberg-Marquardt (LM) optimization. A number of simulation comparison studies are now being carried out in order to verify the approach that has been presented, and a number of investigations are currently being carried out in order to evaluate the efficiency and dependability of various kinds of fans.

This suggested framework, in contrast to many traditional techniques of monitoring, does not need any training phases or predetermined criteria to be in place. Instead, it performs real-time adjustments to the alarm trigger level in order to guarantee that it is appropriate for the operating circumstances that are now in effect. In order to provide evidence that the technique being suggested is successful, an integrated measuring and monitoring system will be established. Experiments have shown that methods for online monitoring of cooling fans that are guided by this model are creative [16].

According to a study by Azzeddine Dkhane et al., the application of a Convolution neural network (CNN) can be another good technique to predefined fault using vibration measurement and signal without feature extraction.In this technique normalized vibration signal are changed in to 2-D data set known as vibration image and these images are used as input to CNN for detecting problem in machines like cooling fan[17].The implementation involves different image sizes,training and testing data sets.

Giuseppe Ciaburro's article delves into machine fault detection techniques, exploring a range of machine learning algorithms. Detecting faults before machine failure is crucial to avoid costly breakdowns and significant financial losses for companies. Different machine learning algorithms, such as Artificial Neural Network models, Convolutional Neural Networks, and Recurrent Neural Networks, are extensively employed for various applications, specifically in identifying machine problems [18].

3. Proposed Method

3.1 Proposed flowchart

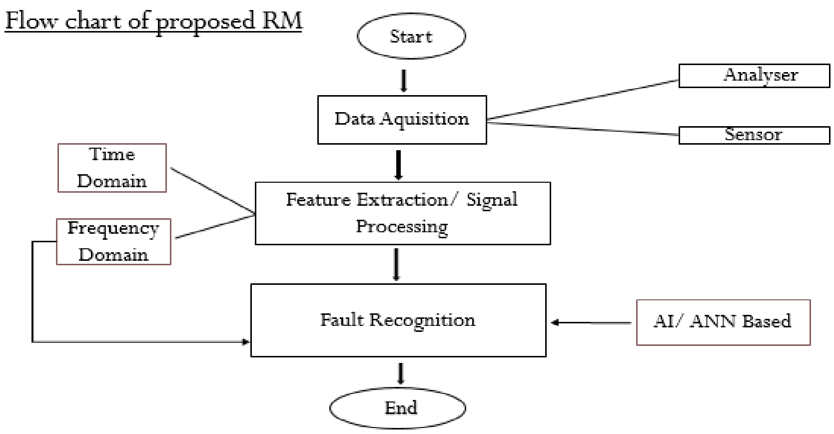


Fig 2. Proposed flowchart

3.2. Introduction to Condition Monitoring

Effective monitoring of expensive assets is crucial for maximizing their lifespan and ensuring their security [1]. However, many existing condition monitoring systems inundate engineers with excessive data, potentially leading to the oversight of critical health indicators. Addressing this issue requires the development of a condition monitoring architecture that can efficiently detect, diagnose, and anticipate abnormalities, while extracting pertinent information from the condition data.

The ultimate objective of conducting maintenance checks and upkeep on machines and equipment is to enhance their availability and reliability, thereby ensuring optimal performance throughout their entire lifespan, while also maintaining cost efficiency [2].

To determine whether a piece of machinery requires servicing, condition monitoring must first assess its current state and the rate of change of its monitored characteristics. This assessment can be performed continuously or periodically [3, 4], with quantifiable parameters monitored either in real-time or at predetermined intervals.

For the purpose of detecting maintenance concerns in spinning machinery, a specialized PM software has been developed. This unique reference encompasses smart PM, condition monitoring, inspection, and troubleshooting for various components, potentially leading to improved maintenance management techniques.

Among the many components involved in the construction of a whole system are pumps, motors, gears, bearings, chains, pipes and valves, couplings, seals, fans, lubrications, lifting gear, hydraulics, pneumatics, compressors, steam, and electrical systems. Implementing preventive maintenance (PM) and condition monitoring techniques can be highly beneficial, involving regular inspections of frequently-used components to identify and prevent potential issues. Such maintenance techniques enable industries to establish and enhance comprehensive PM plans [4].

3.3. Observation of Machine Conditions With Intelligence

ICM employs automated analysis of equipment status, using data from training sets to enable remote connection for smooth and effective operation and timely problem notifications [5]. The Intelligent Condition Monitoring (ICM) system utilizes Artificial Neural Networks (ANNs), known for their adaptable and scalable operation, to perform data analysis[4,5].

The primary objectives of Intelligent Condition Monitoring are twofold: first, to detect abrupt changes in equipment condition that may lead to catastrophic failure, and second, to identify early signs of potential failures to facilitate predictive measures and corrective actions. While both reasons are significant, the detection of sudden changes holds greater importance.

ICM efficiently assesses equipment state through automated knowledge processing, while also enabling remote connections, essential factors for the success of intelligent condition monitoring. The system's capabilities encompass remote access, automated reporting, advanced diagnostics, performance models, vibration diagnostics and display, data playback, email and SMS alert functionalities, as well as temporal pattern matching to identify issues.

3.4. Examination of Vibrations

Excessive vibration in rotating equipment can cause severe damage to its rotary elements, bearings, shafts, and other components. To address this issue, regular inspections and vibration analysis are necessary. Vibration analysis is commonly employed to diagnose various problems in rotating equipment, including imbalance, looseness, misalignment, gear tooth defects, bearing failures, and system resonance [6]. Readings are taken and recorded at predetermined intervals to establish a baseline.

Maintenance managers then compare the collected data against the baseline to identify deviations. When vibrations exceed acceptable levels, a thorough analysis is conducted to determine the root cause, and appropriate measures are taken to resolve the problem. This proactive approach not only reduces the need for unplanned repairs but also ensures smooth and uninterrupted operations in manufacturing and other facility activities during replacements. For a better understanding of the vibration analysis procedure, refer to Figure 3.

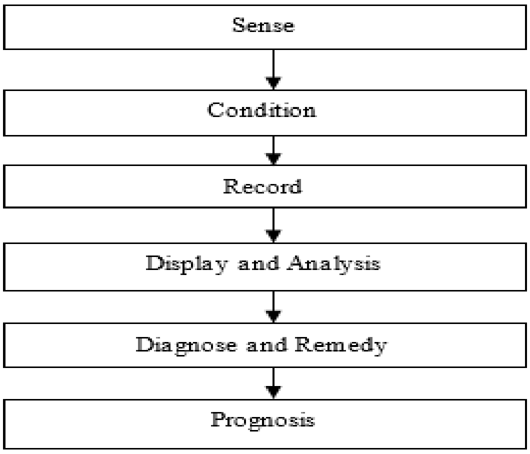


Fig 3. Method for Analyzing Vibrational Signals.

Step 1: The first thing that needs to be done is to use a transducer to feel the vibration experienced by the structure to measure the different characteristics related to vibration. A transducer is a device that takes an input of vibration and outputs a signal of some kind, often electrical but sometimes optical or mechanical, that is proportional to the vibration as the user feels.

Step 2: Before recording, the signal that was collected from the transducer has to be conditioned in the module known as the condition module. Filtering, in which certain signal parts are emphasized or suppressed, may accomplish this. A preamplifier, which comprises a filter and an integrating circuit, is often used to condition the signal before it is amplified.

Step 3: The Record module is then used to record the data on the electronic data collector. They make it possible to monitor vibration at a variety of point intervals as well as periodic ones.

Step 4: Measured variables must be shown accurately in the Display and Analysis phase for spectrum analysis.

Step 5: During the Diagnosis and Repair procedure, each machine failure produces a distinct set of vibrational components that may be utilized to pinpoint the source of the problem. Possible vibration causes include imbalance, misalignment, bearing issues, mechanical sloppiness, resonance, and faulty gears. The vibration is affected by the dynamics of the machinery, the operating circumstances, the many defects, and the speed fluctuations, which makes the correlation process more difficult. To remedy a situation, first, the problem must be located. Then, after the problem has been located, corrective action, which might take the form of repair or replacement, must be implemented.

Step 6: The prognosis is the last step of vibration analysis. This is where an estimate of how long the machine has left to live can be made.

3.5 Proposed Method

The design and implementation of intelligent systems have become important parts of how industries develop new products and improve the ones they already make [7, 8]. A neural network is a parallel system that can solve problems that can't be solved by linear computing [8]. In the next figure, labelled "Figure 4," you can see a mathematical representation of an artificial neural network. This system uses ANN, and the data flows from input units to output units and are dynamically constructed in a feed-forward fashion over the runtime. It is possible that the data processing will occur across several units (layers), but there will be no feedback links present. This indicates no connections between the outputs and the inputs of units located on the same layer or levels above [9].

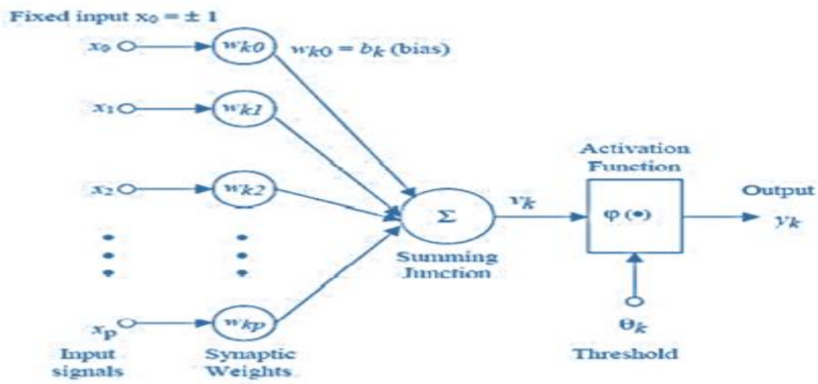


Fig 4: Modeling of Artificial Neural Networks Mathematically.

3.5.1. Neural Network with Back Propagation

Finding the smallest value of the error function inside the weight space is the goal of the backpropagation algorithm, which uses the gradient descent search technique to accomplish this. A solution to the learning issue may be regarded to be any collection of weights that can reduce the error function to its minimum value. In order for the method to accomplish this goal, each step in the process involves an iterative determination of the gradient of the error function. Therefore, in order to guarantee that this method is effective, the error function has to be continuous and it also needs to be differentiable [10].

The sentence provides an accurate definition of the sigmoid function. Regarding backpropagation networks, the sigmoid function is often used as an activation function.

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

In stochastic neural networks, the constant c may be chosen at will, and the temperature parameter is denoted by its reciprocal, 1/c. Figure 5 demonstrates how the shape of the sigmoid changes as a function of the c-parameter. For the values of c equal to 1, c equal to 2, and c equal to 3, the graph takes on the shape of a sigmoid. [11] In the limit, when c approaches infinity, the sigmoid's form approaches that of the step function. 1 The sigmoid function gets close to a step function near the origin. After reading this content, a reader should be able to generalize all the equations for a variable c. For the sake of simplicity, we'll set c = 1 for the rest of the chapter's derivations so that everything adds up to 1. The sigmoid function s1(x) shall hereafter be abbreviated as s. (x) [12].

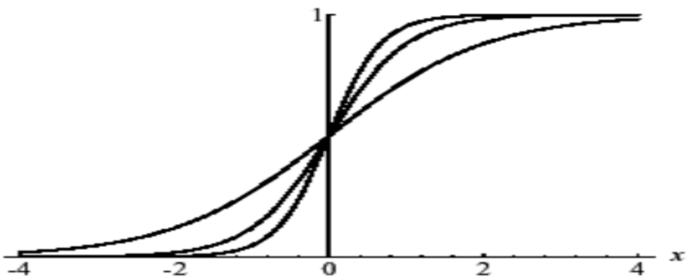


Fig 5: A Network with Three Simplified Sigmoids (for c = 1, c = 2, and c = 3)

The derivative of the sigmoid function concerning the independent variable x,

$$\frac{d}{dx}s(x) = \frac{e^{-x}}{(1 + e^{-x})^2} = s(x)(1 - s(x))$$

3.5.1.1 Architecture of BPNN. The Back Propagation Neural Network's construction is seen in Figure 6, which may be found here. The mistake, which was later passed on to following generations, may be seen here once again.

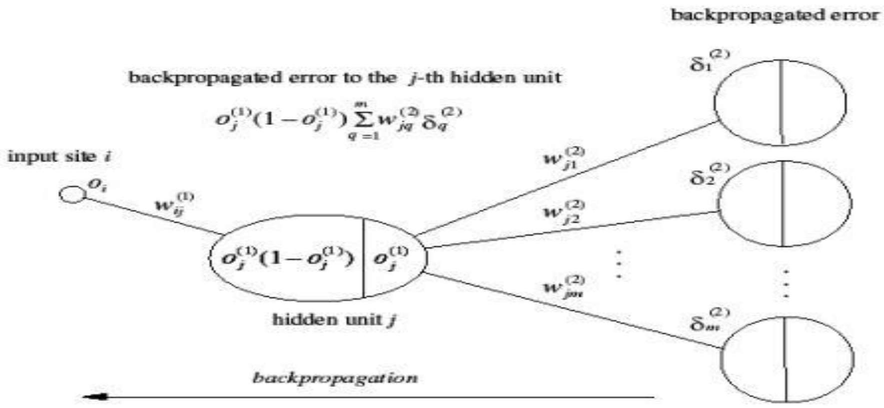


Fig 6: The framework of the Back Propagation Neural Network.

When the value of the error function has fallen to a point where it is regarded acceptable, the BPNN will be terminated. This will happen when the error function has reached its minimum value. Following are the actions that need to be taken in order to dismantle the BPNN into its component parts:

i. Computation carried out in the forward-looking or feed-forward orientation.

ii. Propagation from the input layer to the output layer in reverse.

iii. Transmission of the signal to the buried layer by backpropagation.

iv. The dissemination of the latest weight update.

3.5.1.2. The BPNN algorithm is as follows. The following is an explanation of the algorithm for the backpropagation neural network:

1. Initialize the Network: At the beginning of the training process, the neural network's weights and biases are initialized randomly. These weights and biases are the parameters that the algorithm will update during training to minimize the error.
2. Forward Pass: In this step, the input data is fed into the network, and its activations are calculated layer by layer until the output layer is reached. Each node in the network computes its activation based on the weighted sum of inputs and passes it through an activation function (e.g., sigmoid, ReLU, tanh). The output of the network is compared to the ground truth labels using a loss function (e.g., mean squared error, cross-entropy).
3. Compute Loss: The difference between the predicted output and the actual target (ground truth) is measured using the chosen loss function. The goal of training is to minimize this loss.
4. Backward Pass (Backpropagation): This is the crucial step in the algorithm. During the backward pass, the algorithm calculates the gradients of the loss with respect to the network's weights and biases. It starts from the output layer and goes backward through the network to compute these gradients.
5. Update Weights and Biases: After obtaining the gradients, the algorithm uses an optimization technique (e.g., stochastic gradient descent, Adam) to update the weights and biases of the network. The gradients tell us the direction in which the parameters should be adjusted to reduce the loss.
6. Repeat: Steps 2 to 5 are repeated for each mini-batch of training data multiple times (epochs) until the loss converges to a satisfactory level or a predetermined number of epochs is reached.
7. Validation: After training, the model is validated on a separate validation set to assess its performance on unseen data and tune any hyperparameters if necessary.
8. Testing: Finally, the model is tested on a completely separate test set to evaluate its generalization performance.

3.5.2. Neural Network Based on the Radial Basis Function (RBFNN)

A Radial Basis Function Neural Network (RBFNN) is a type of artificial neural network that uses radial basis functions to model complex relationships between input and output data. Unlike traditional feedforward neural networks with hidden layers, RBFNNs have only two layers: an input layer and an output layer. The main components of an RBFNN are the radial basis functions and the output layer.

Here's how an RBFNN works:

Input Layer: The input layer receives the input data, which could be a vector representing features from a dataset.

Radial Basis Functions (RBFs): The radial basis functions are used to transform the input data into a higherdimensional space. These functions compute the similarity (distance) between the input data and a set of learnable centroids. The most commonly used RBF is the Gaussian function:

$$\emptyset_i(x) = e^{-\frac{\|x-\mu_i\|^2}{2\sigma_i^2}}$$

Here, μ_i is the center (centroid) of the i-th RBF, and σ_i is a width parameter that controls the spread of the function. The values of μ_i and σ_i are adjusted during the training process.

Hidden Layer (Activation Layer): The output of each RBF serves as the activation of a corresponding neuron in the hidden layer. The hidden layer is not trainable; it simply computes the activations based on the distance between the input data and the centroids.

Output Layer: The output layer performs a weighted sum of the activations from the hidden layer. The weights between the hidden layer and the output layer are learnable parameters that are adjusted during training. The output of the network is the final prediction made by the RBFNN.

Training an RBFNN involves determining the centroids μ_i and widths σ_i of the radial basis functions and optimizing the weights between the hidden and output layers to minimize a specified loss function, usually mean squared error or cross-entropy.

3.5.2.1. RBFNN's structural framework. Each hidden node has a bell-shaped curve, indicating that it represents a radial basis function in the feature space that is centred on a vector [5]. Connecting the input nodes to the hidden nodes does not have any weights. RBFNN's structure is shown in Figure 7 below.

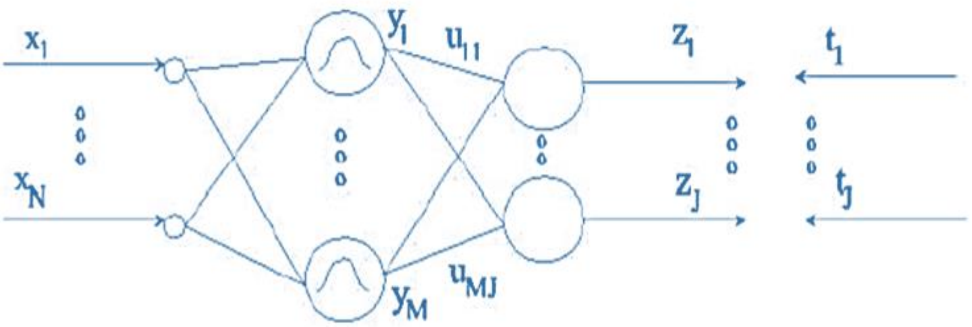


Fig 7: Structure of Recurrent-Biased Neural Networks.

After passing through the nodes of the radial basis function, the input vector is sent to the next hidden node, where it is fed again.

$$y_m = f(x) = \exp\,[-\left||X - c_m|\right|^2 \;/\; (2\sigma^2)]$$

Where $\left||X - c_m|\right|^2$ is the square of the distance between the input feature vector x and the centre vector cm for that radial basis function

The radial basis functions generate the outputs denoted as y and m. In a two-dimensional feature space, these functions exhibit a specific shape, as illustrated in the straightforward graph displayed in Figure 8. They are called radial basis functions because the values at equal distances from the center in all directions are identical within their sets.

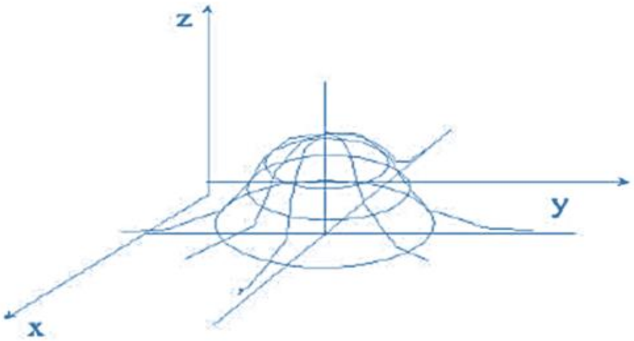


Fig 8: Radial Basis Functions are formed from scratch.

3.5.2.2. The RBFNN algorithm is shown here.

To utilize the stated algorithm, you need to download the data file first. This file contains N, M, J, and Q values, along with the feature vectors and their corresponding target vectors.

Here's a step-by-step breakdown of the algorithm:

Step 1:

- Read the data file to obtain the feature vectors and their target vectors.
- Input the number of iterations (I).
- Set I = 0.
- Use Q centers of Radial Basis Functions (RBFs) as exemplar vectors.
- Set M = 2Q.
- Randomly initialize the weights of parametric variables u and mj within the range of -0.5 to 0.5.

Step 2:

- Determine the average distance between centers.
- Remove any centers that are within a specific distance of another center.
- Select M centers as the final set of centers.
- Calculate and randomly select the values for umj within the range of -0.5 to 0.5.

Step 3:

- Determine the values of ym and zj.

Step 4:

- Calculate the error (E) using the earlier discovered equation.
- Update all parameters umj for every m and j during the active iteration.

Step 5:

- Calculate ym and zj again.

Step 6:

- Obtain the most recent value for E.
- If the new E is lower than the prior E, increase the value of I; otherwise, decrease it.
- If the new E is lower, replace the previous E with it.

Step 7:

- If the value of I is less than the input I, increment I, and go back to Step 4 for another iteration. Otherwise, the algorithm terminates.

3.5.3 Self-Organizing Map (SOM)

A Self-Organizing Map (SOM), also known as a Kohonen map, is an unsupervised artificial neural network algorithm used for dimensionality reduction, visualization, and clustering of high-dimensional data. It was introduced by Teuvo Kohonen in the 1980s. SOMs are particularly useful for exploring the underlying structure and patterns in complex datasets.

Here's an overview of how a Self-Organizing Map works:

Initialization: The SOM starts with an array or grid of neurons, each having a weight vector of the same dimensionality as the input data. The weight vectors are initialized randomly or using a specific initialization technique.

Input Data: The SOM receives the input data, which could be high-dimensional data points or feature vectors.

Competition (Best Matching Unit - BMU): For each input data point, the SOM identifies the neuron whose weight vector is most similar to the input data. This neuron is called the Best Matching Unit (BMU). The similarity is typically calculated using a distance metric like Euclidean distance.

Neighborhood Function: The BMU and its neighboring neurons form a neighborhood in the SOM grid. The neighborhood function defines the topological relationship between neurons, and it decreases with increasing distance from the BMU. The most common neighborhood function is Gaussian, but other functions can be used as well.

Adaptation: The weights of the BMU and its neighboring neurons are adjusted (updated) to become more similar to the input data point. The amount of adjustment is influenced by the learning rate (a hyperparameter that decreases over time during training) and the neighborhood function. This step allows the SOM to self-organize and adapt its neurons to the input data distribution.

Iterations: Steps 3 to 5 are repeated iteratively for a fixed number of epochs or until convergence. As the training progresses, the SOM organizes itself into a low-dimensional representation of the input data, where similar input data points are mapped to nearby neurons in the SOM grid.

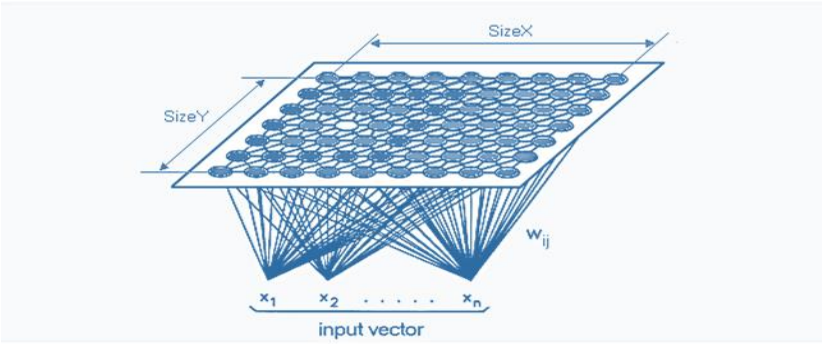


Fig 9. The architecture of a Self-Organizing Map (SOM)

3.5.3.1 What happens in SOM?

The data points that make up a set acknowledge one another's existence by vying to be included in a visual representation of the data. It is necessary to initialize the weight vectors before beginning the SOM mapping procedure. Afterwards, a sample vector is selected randomly, and the weight vector map is investigated to determine which weight vector corresponds to that sample the closest. Extra weight vectors are located fairly near to and right adjacent to every one. The randomly picked weight receives an improvement in its capability of approaching the sample vector's degree of similarity, which is a benefit for the overall analysis. The neighbours of that weight are likewise rewarded by being allowed to evolve into progressively similar vectors to the one chosen to serve as the sample.

3.5.3.2 Algorithm:

1 The weights of each node are set to zero. 2. A random vector is selected from the dataset used for training. Third, the weights of each node are compared to the input vector to determine which nodes are most similar. BMU is shorthand for "Best Matching Unit" and describes the victorious node. After that, the BMU's immediate vicinity is determined. In time, fewer people will be your neighbors. Five, the winning weight improves its similarity to the sample vector as a reward. Similarities between the sample vector and its neighbour increase. A node's weights are modified to a greater extent the closer it is to the BMU, and a lesser extent, the further away it is from the BMU. To do this, we will iterate through step 2 for N times.

4. Implementation

4.1 Hardware requirement

15.6-inch (39.62-centimeter) Full High-Definition (FHD) Dell Inspiron 3584 Laptop (7th Generation Core i3-7020U/4GB/1TB HDD/Windows 10 With MS Office/Intel HD Graphics/Silver) 2.29 GHz Intel Core i3-7020U 7th Gen CPU; Windows 10 operating system; 4 GB DDR4 RAM; 5 400 rpm hard drive; 15.6-inch screen; Intel HD Graphics (Integrated); 2.2 kilogramme (kg) laptop; 15.6-inch display; one year guarantee from the manufacturer. Customer care: 1800 425 2067, Display Resolution Maximum: 1366x768; Human Interface Input: Keyboard; Hard Disk Description: Ssd; Wireless Communication Technology: 802.11 Ac; Software Included: Microsoft Office Home And Student 2019

4.2 Software requirement

MATLAB is proprietary software developed by MathWorks; obtaining, installing, and activating it requires a license. There are two new versions of MATLAB published every year, and the titles of these releases are formed of the letter R, the year of the release, either a or b. Arch Linux does not yet get official support.

4.3 Dataset

4.3.1 Vibration Measurement Procedure: Vibrations were measured on the motor bearings and the fan bearings of the bag filter fan of a cement industry. These measurements were taken in all three directions (horizontal, vertical, and axial) at four different pickup points: the drive end of the motor, the non-drive end of the motor, the fan drive end, and the fan non-drive end. Because the vibrations produced by the machines will only be reflected via their bearings, these pickup sites are sufficient for carrying out appropriate machine monitoring. An accelerometer was fixed to each previously outlined location to get accurate readings.

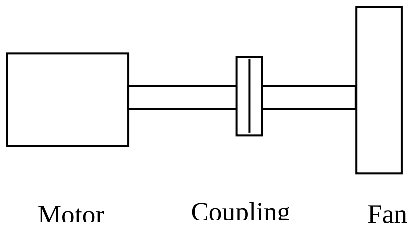
The captured signals were examined using an FFT analyzer in the frequency domain. The analyzer gave a reading of the overall amount of vibration in the recorded signal. These vibration data saved in the analyzer may be downloaded to a desktop computer and further analyzed using software designed specifically for vibration analysis. At last, the trend graphs and frequency spectrums were acquired at various places in each of the three directions to conduct more research.

Table 1. Sample of dataset

		Motor Non-Drive End			Motor Drive End			Fan Non-Drive End			Fan Drive End		
Unit		A	H	V	A	H	V	A	H	V	A	H	V
2	1*rpm	2.525	3.297	5.752	4.279	3.911	1.324	3.7	1.859	2.859	4.086	5.191	3.595
	2-3*rpm	0.388	2.753	0.539	0.596	2.613	1.806	1.083	2.613	2.648	0.728	1.263	1.64
	4-6*rpm	0.552	0.517	0.587	0.452	0.27	0.741	0.693	1.394	0.684	1.052	1.394	0.798
32	1*rpm	8.488	47.7	6.699	9.33	49.38	3.034	8.137	40.97	13.96	8.733	44.05	13.05
	2-3*rpm	1.048	2.981	1.692	0.96	2.718	2.42	1.149	5.927	3.051	0.916	2.42	0.829
	4-6*rpm	0.82	0.388	0.579	0.776	0.258	0.815	1.912	1.464	0.868	1.447	0.978	0.956
36	1*rpm	7.985	47.98	7.942	9.56	51.369	4.589	6.325	48.684	8.589	6.887	48.254	10.989
	2-3*rpm	0.993	3.621	0.854	1.456	3.569	1.715	1.025	3.895	2.672	0.785	1.754	1.025
	4-6*rpm	0.791	0.473	0.659	0.758	0.321	0.767	1.243	1.501	0.798	1.269	1.225	0.998
40	1*rpm	7.576	48.26	9.54	9.61	53.31	5.577	4.069	56.12	3.63	5.191	51.35	8.137
	2-3*rpm	0.921	4.261	0.445	1.938	4.033	1.035	0.903	2.946	2.315	0.596	1.105	1.219
	4-6*rpm	0.715	0.587	0.798	0.741	0.379	0.715	0.557	1.587	0.754	1.039	1.464	1.048

4.3.2 Machine Diagram :

Cement Industry Fan



Machine Specifications:

- Motor- 35Kw, 1480 rpm, 03 phase, 415 volts
- Fan - No. of vanes 10

Frequency Spectrum for Motor Non Drive End Horizontal (MNH)

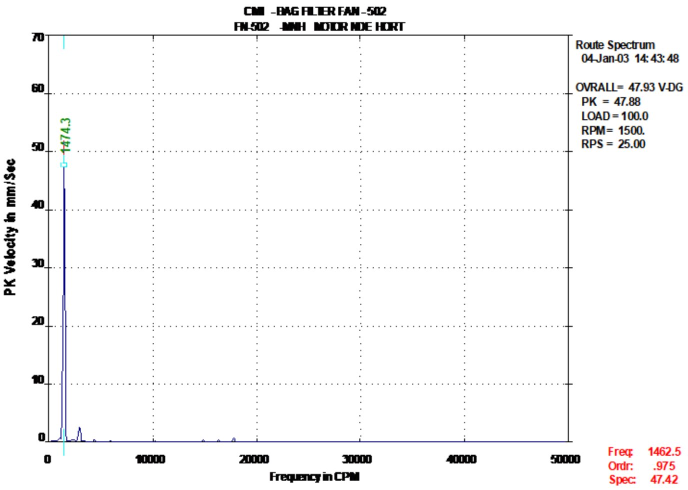


Fig 10 : Machine setup & Typical Friuency Spectrum showing Unbalance.

4.4 Parameters for implementation

Table 2: Parameters for implementation

S. No.	Parameters	Number
1	Number of epoch	10
2	Number of hidden layer	18
3	Input layer	24
4	Output layer	12
5	MATLAB	20 version
6	Dataset	Motor Non Drive End, Motor Drive End, Fan Non Drive End, Fan Drive End
7	Direction	Axial (A), Vertical (V), Horizontal (H)
8	Frequency components	1*rpm, 2-3*rpm ,4-6*rpm
9	Unbalance Value	1,2,3,4,5,6,7,8,9,10,11,……..,108,109.

4.5 Simulation model

ANNs are computer systems inspired by brain neural cells. ANN's major function is linear and nonlinear approximation, data clustering and classification, or model simulation. Feed-forward and back propagation are used to train neural networks. FFBPN learns and maps input-output relationships. The FFBPN learning rule adjusts weight and threshold values to minimize error. It's a complex relationship between a network's input and output values. Each node or neuron's value is decided by network input. Each input signal's line weight is multiplied. FFBPN is used because of its high prediction accuracy and ability to learn from measured data.

Training Algorithm: The Levenberg–Marquardt algorithm was created jointly by Kenneth Levenberg and Donald Marquardt. Fast convergence. This approach trains small and medium-sized artificial neural network challenges. With the help of the ANN toolbox in MATLAB,2020a. ANN was successfully implemented. Extensive research was performed to determine the most suitable network architecture for the artificial neural network configurations as shown in figure 11. This was achieved by adjusting the hidden layer's level and its neurons' frequency. Multiple networks of varying architectures were trained for a certain number of cycles and then tested using a given set of input and output parameters. Figure 12 shows the implementation of ANN model for run time training with input and output data.

Network Type: Feed Forward Back Propagation.

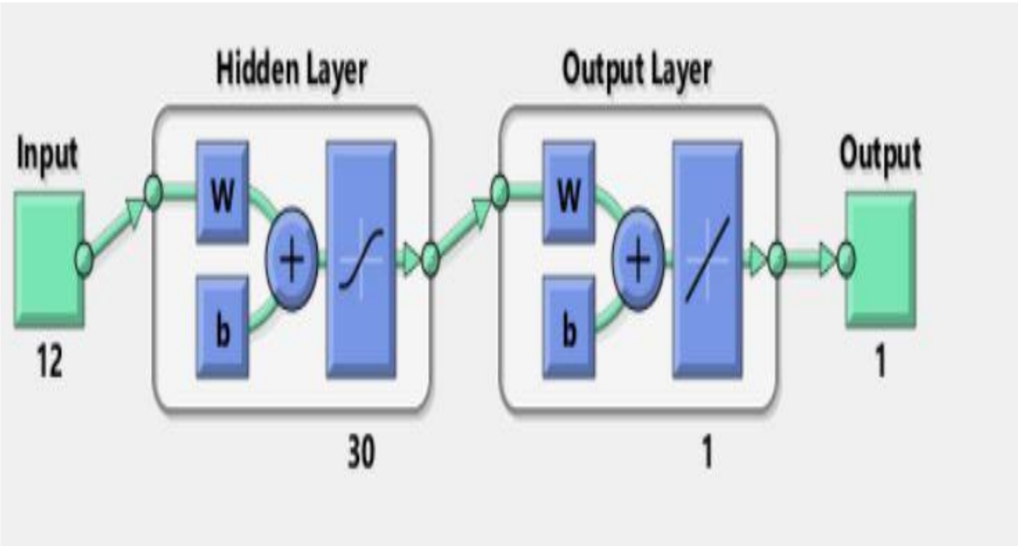


Fig 11. architecture for the artificial neural network

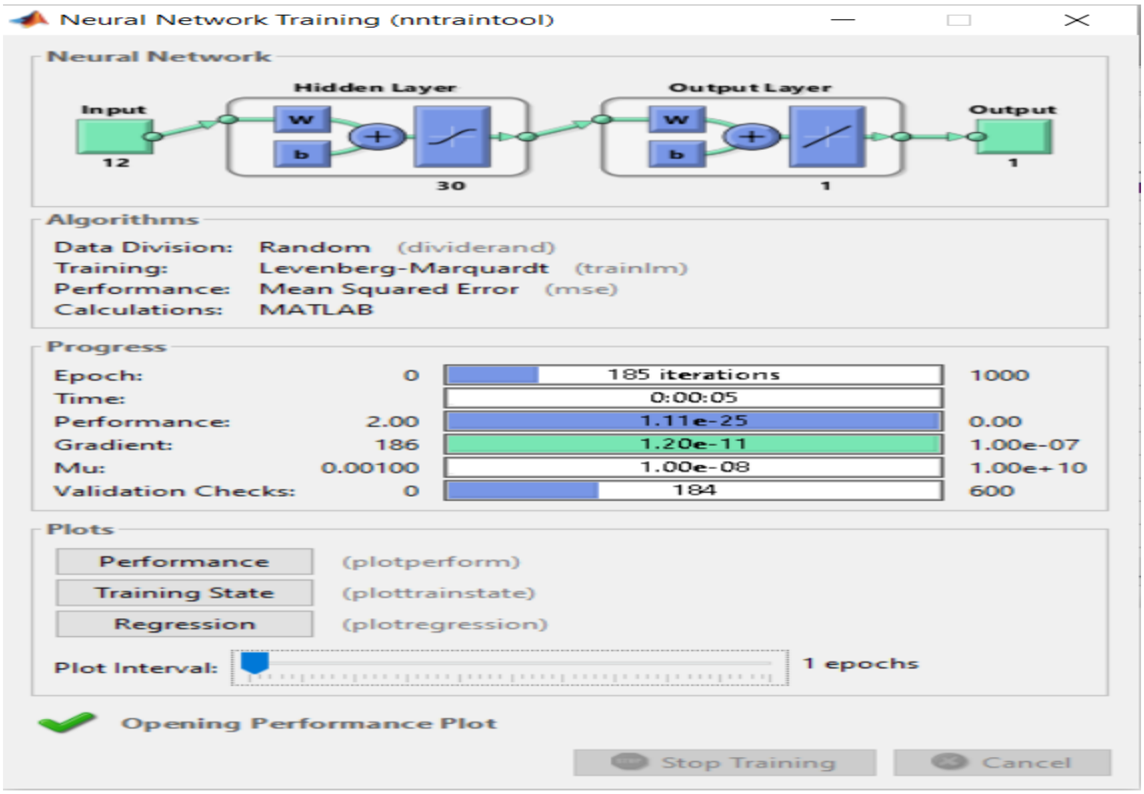


Fig 12: Implementation of the ANN model

5. Result

5.1 Validation result

For a neural network, an epoch is the time it takes to complete a full training cycle. It only ever uses all of the information collected in each epoch once. Combined completions of passes in both directions are counted as a single pass. Figure 13 shows the validation performance of training data and found that the best validation performance was at epoch 54 with a 1.567 mean square error.

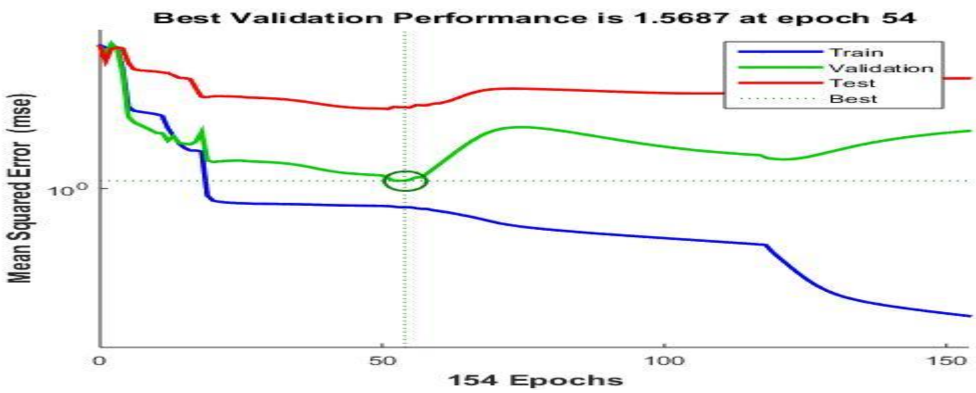


Fig 13 Validation performance of the ANN Model

Regression (R) in ANN represents how the ANN predicts an output variable with the set of input variables. Higher values R means the model correlates with the training data. Figure 14 shows R values for training, validation, and testing, which were found to be 99 %. This shows that the model can predict the output with 99 % accuracy.

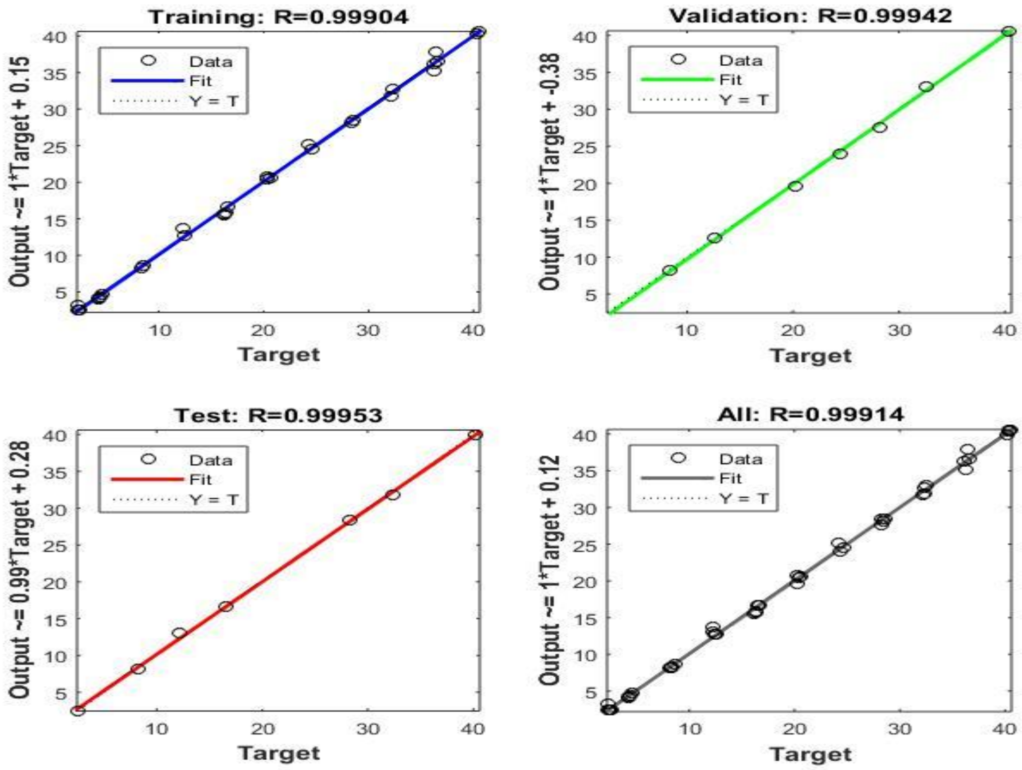


Fig 14 Regression Analysis for ANN model

5.2 Result of the neural network model

High vibration levels are due to the problem of machine (Fan) unbalance, which is confirmed by frequency analysis and a typical frequency spectrum shown in Figure 10. Unbalance generally occurs due to material coating on blades, and blade wear and usually expressed in gm-cm.

After the training, the ANN model is prepared and tested for the different input values associated with 02 unit unbalance and 32 unit unbalance.

Table 3 shows the ANN model's predicted values and actual values corresponding to input values.

Predicted Unbalance (units)	Actual Unbalance (units)
2.602944	2
2.38963	2
3.444795	2
2.671883	2
32.60446	32
32.23603	32
31.91953	32
30.96941	32

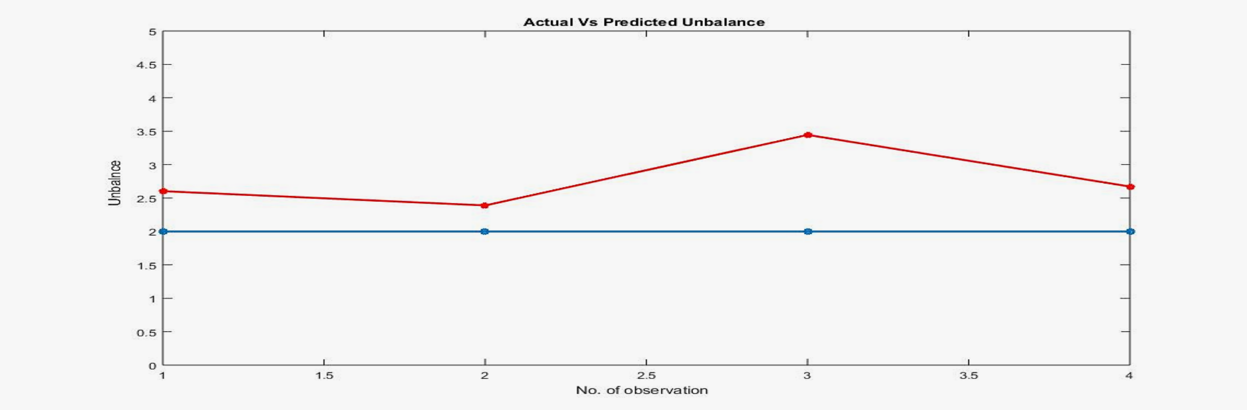


Fig 15 Graphical variation of predicted values with actual values of unbalance 2 **(**units)

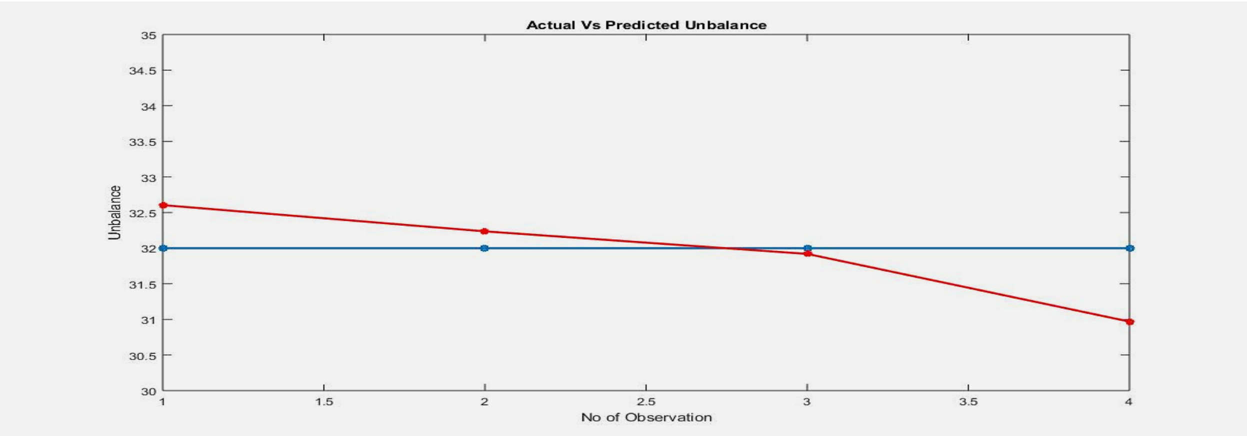


Fig 16 Graphical variation of predicted values with actual values of unbalanced 32 **(**units)

Table 4. Result For Fan Non-Drive End, Fan Drive End, Motor Non-Drive End, and Motor Drive End

Type of Fault :	**Unbalance**			
Neural Network Model	**Training Time**	**Testing Time**	**Test- Success (%)**	**Accuracy (%)**
Multilayer Feed Forward Neural Network	5 sec	2 sec	95	99.9
Radial Basis Function (RBF)	10 sec	20 sec	60	60
Self-Organizing Map (SOM)	20 sec	5 sec	50	55

The table shows that multilayer feed-forward neural network is showing better prediction results compared to radial Basis function and self-organizing map neural network. The possible reasons for the above results are that in the case of radial basis function (RBF), increasing the number of hidden layer neurons in an RBF network makes the network more complex. As a result of flaws in its structure and training algorithm, the regular RBF cannot represent highly nonlinear systems. RBF network classification is slower than Multilayer feed-forward because every node in the hidden layer must compute the RBF function for the input sample vector. Similarly, in the case of a Self-Organizing Map (SOM), the primary problem of the SOM is that it requires neuron weights to be necessary and sufficient to cluster inputs. When a SOM gives inadequate data or too much noise in the form of weights, the clusters produced by a SOM may not be completely representative of the input. SOM make it challenging to map distinct groupings properly. Instead, map anomalies cause comparable groupings to appear in different regions. Clusters are typically separated, generating zones of comparable neurons. This can be avoided by properly initializing the map, but not if the final map's state is unclear.

6. Conclusion

This study shows methods for developing and comparing three Artificial Neural Networks algorithms based on the Back Propagation algorithm, Radial Basis Function, and Self-organizing network. These techniques are presented as part of this paper. Although the idea has been tested on industrial samples for industrial fan fault detection, it is adaptable enough for condition monitoring in other applications with minimal modifications. This paper aims to highlight the application of Artificial Neural Network (ANN) models in condition monitoring of industrial fans using vibration signals and, in turn, comparing the performance based on training and testing, quantifying and classifying the faults, test success and accuracy.

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