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Intelligent Condition Monitoring of AIRBLOWER using Artificial Neural Network with Genetic Algorithm

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Abstract. Fault Detection in machinery is done by regular condition monitoring and vibration analysis. Automatic fault detection techniques are reliable, fast and accurate that can be applied to find solutions to numerous problems. Intelligent condition Monitoring System for fault detection based on dynamic Multilayer Feed Forward Neural Network is an automated system that detects errors in machinery based on trained neural network model. The objective of the current investigation is to introduce a novel approach to Intelligent Condition Monitoring System based on Artificial Neural Networks optimized by Genetic Algorithm. This work uses the implementation of Back propagation Neural Network and Radial Basis network and genetic algorithm is used for optimization in selecting the network. Genetic algorithms are a class of optimization procedures which are good at exploring a large and complex space in an intelligent way to find values close to the global optimum. An ANN was optimized for efficient fault diagnosis in machinery equipment. The network is dynamically generated basing on the requirement of input and output nodes and number of hidden layers can be applied to numerous problems. Also this system is an Online Web-based conditioning monitoring system to be applied successfully in preventing machinery failures and exclusively tested on Air blower. The results are compared with manual calculations and found to be accurate and reliable.

1. Introduction to Condition Monitoring

Condition monitoring is important for safely prolonging the life of costly assets [1]. However, many condition monitoring systems produce too much data for engineers to view and assess, leading to useful indicators of health being overlooked. This could be solved with a condition monitoring architecture capable of anomaly detection, diagnosis, and prognosis, extracting as much information as possible from condition data. Maintenance of machinery equipment is carried out to increase the availability and reliability, so that it will continue to operate satisfactorily for the entire life-cycle of the equipment with required cost effectiveness [2].

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Condition monitoring involves determining the condition of a machine and its rate of change of measured parameters in order to determine the maintenance requirement. The condition of machine may be determined continuously or at regular 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. The maintenance techniques allow setting up and improving a preventive maintenance program in any industry [4].

2. Intelligent Condition Monitoring

Intelligent Condition Monitoring (ICM) system offers a way of creating architecture, capable of analyzing the data using Artificial Neural Network which works in a flexible and extensible way.ICM evaluates the condition of machinery by automating the knowledge based on training sets and also allows users to connect remotely to system to assist them in the smooth and efficient running of machinery and will alert you when there is a problem [5]. Intelligent Condition Monitoring is carried out for two main reasons: to detect sudden changes in condition that could lead to catastrophic failure and to identify the early onset of incipient failures so that a prediction can be made and remedial measures suggested. The System Features are sophisticated diagnostics, Temporal pattern matching of faults, Performance models, Vibration diagnostics and display, Replaying of data, Remote access, Automated reports, and Email and SMS notifications.

2.1. 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 [6]. Generally periodic readings are taken and recorded. Maintenance personnel then compare these readings 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.

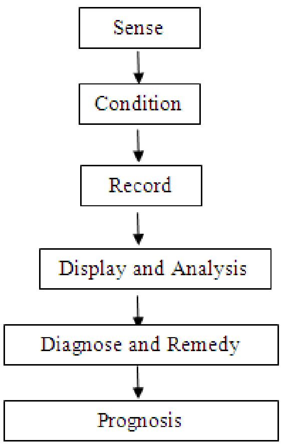

Figure 1. Vibration Analysis Procedure.

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 point and periodic 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.

3. Dynamic Multilayer Feed Forward Neural Network

Designing and implementing intelligent system has become a crucial factor for the innovation and development of better products for industries [7]. A neural network is a parallel system, capable of resolving paradigms that linear computing cannot [8].The Mathematical model of Artificial Neural Network is as shown in Figure2. This system implements ANN, where the data flows from input to output units is strictly feed forward created dynamically at runtime. The data processing can extend over multiple (layers of) units, but no feedback connections are present i.e., connections extending from outputs of units to inputs of units in the same layer or previous layers [9].

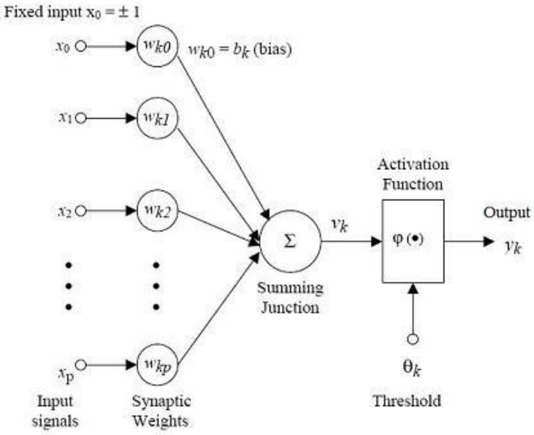

Figure 2: Mathematical model of Artificial Neural Network.

3.1. 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 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.

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

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 3. 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]

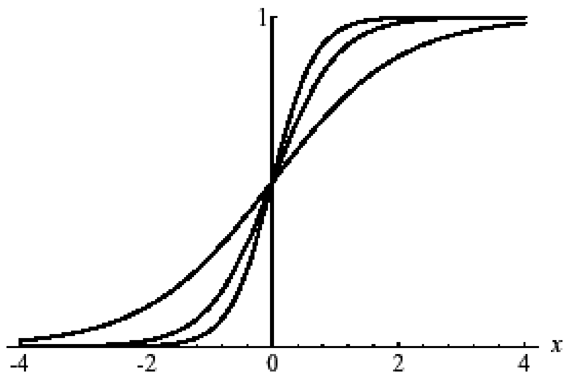

Figure 3: Three sigmoids (for c = 1, c = 2 and c = 3) Network.

The derivative of the sigmoid with respect to x,

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

3.1.1. Architecture of BPNN. Figure 4 shows the architecture of Back Propagation Neural Network. Here back propagated error is fed back.

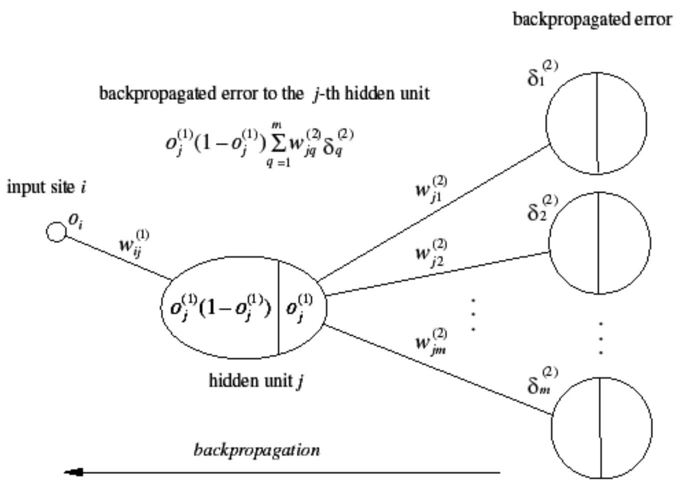

Figure 4: The architecture of Back Propagation Neural Network.

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:

i. Feed-forward computation
ii. Back propagation to the output layer
iii. Back propagation to the hidden layer
iv. Weight updates

3.1.2. Algorithm for the BPNN. The Algorithm for Back Propagation Neural Network 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]

3.2. Radial Basis Function Neural Network (RBFNN)
Radial basis functions are embedded into a two-layer feed-forward neural network. Such a network is characterized by a set of inputs and a set of outputs. In between the inputs and outputs there is a hidden layer that consists of processing units called hidden units. Each of them implements a radial basis function.

3.2.1. Architecture of RBFNN. The bell shaped curves in the hidden nodes indicate that each hidden layer node represents a bell shaped radial basis function that is centred on a vector in the feature space.[13] There are no weights on the lines from the input nodes to the hidden nodes .The architecture of RBFNN is shown in Figure 5.

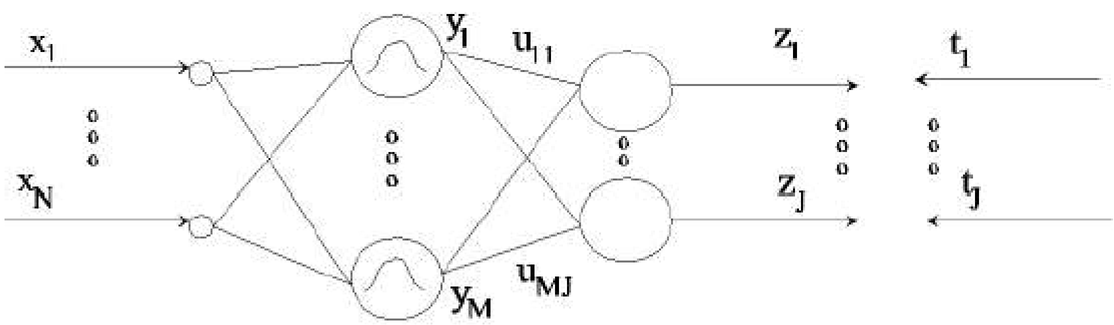

Figure 5: Architecture of RBFNN.

The input vector is fed to each m^{th} hidden node where it is put through the nodes of radial basis function.

$$y_m = f(x) = \exp[-\| X - c_m \|^2 / (2\sigma^2)] \quad (3)$$

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

The values {y }m are the outputs from the radial basis functions. These radial basis functions on a 2-dimensional feature space have the form shown in the simple graph in figure 6. The values equidistant from the center in all directions have the same values; therefore they are called as radial basis functions.

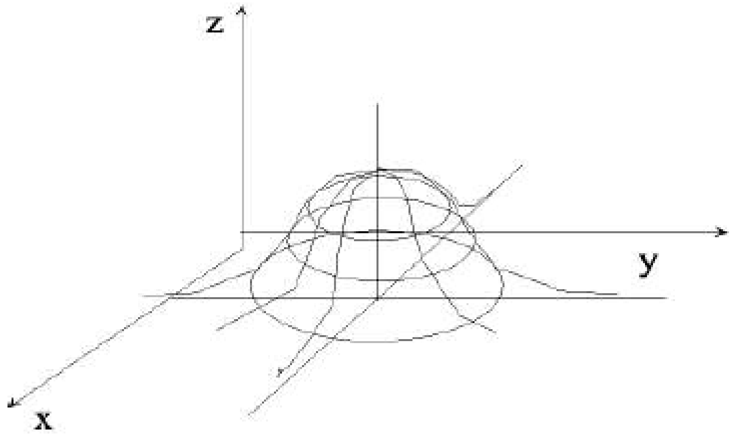

Figure 6 : Radial Basis Functions form.

3.2.2. Algorithm for the RBFNN. To implement the indicated algorithm, the file of data is taken that includes values for N, M, J, Q, the feature vectors and their target vectors, draw the parametric weights {u} mj at random between -0.5 and 0.5, and iterate on the parameters.

Step 1: Read the data file to get N, J, Q, the feature vectors and their target vector, input the number of iterations I, set i = 0, set Q centers of RBF's as the Q exemplar vectors, put M = 2Q.

Step 2. Find average distance between centers, eliminate centers too close to another center, set M as final set of centers, compute , and draw the parameters {umj} at random between -0.5 and 0.5

Step 3. Compute {ym } and {zj }, and then compute E

Step 4. Update all parameters umj for all m and j at the current iteration by above Equation

Step 5. Compute {ym } and {zj}, and then compute the new value for E

Step 6. If new E is less than the old E then increase 0 else decrease it

Step 7. Increment iteration i, if i < I then go to Step 4, else stop

3.3. Advantages of DMFFMM

There are several advantages of DMFFMM: This can perform tasks that a linear program cannot. When an element of the neural network fails, it can continue without any problem by their parallel nature. A neural network learns and does not need to be reprogrammed. This can be implemented in any application. Also this can be implemented without any problem.

4. Optimization using Genetic Algorithm

Genetic Algorithms are search algorithms based on the mechanism of natural selection and genetics that operate without knowledge of the task domain and utilize only the fitness of the evaluated individuals. These are guided by the principles of evolution and natural genetics. In general, three basic operators of the Genetic Algorithms are reproduction, crossover and mutation. During evolution, Genetic Algorithms requires only information that the quality of the fitness value produced by each parameter set. This differs from many optimization methods requiring derivative information or complete knowledge of the problem structure and parameter. Hence, the GA is more suitable to deal with the problem of lacking experience or knowledge than other searching methods.[13]

Genetic algorithms are very simple, robust, randomized global search techniques, have excellent properties for the optimization and do not require any human expert or explicit training data. In particular, when the phenomena being analyzed are describable in terms of the rules for action and learning processes. GAs perform search in complex, large and multimodal landscapes, and provide near-optimal solutions for objective or fitness function of an optimization problem.

4.1. Algorithm for the Genetic Algorithm

Genetic Algorithm is started with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the previous one. Solutions which are selected to form new solutions (offspring) are selected according to their fitness and suitability of getting more chances of reproduction.

Step 1: Input the required parameters which specified values of the traits as matrix. Each column represents a chromosome and each element in that column representing a gene.

Step 2: Set some values based on the values input by the user. The length of the chromosome and start point of each trait is determined.

Step 3: Calculate the fitness, create the children and repeat until the EPSILON-DELTA termination condition is satisfied or MAX_GEN is reached.

Step 4: Compute the fitness function. The fitness function must be chosen so that it is always positive.

Step 5: Determine the most fit and least fit chromosome and the chromosome numbers.

Step 6: Form the mating pool. For this we select as parents the chromosomes that are most fit where each individual gets to mate and randomly pick someone else in the mating pool to mate with.

Step 7: Mutate children & create the next generation

Step 8: Terminate the program when the best fitness has not changed more than EPSILON over the last DELTA generations.

5. Case Study: Air Blower

Air Blowers are used to move air in various industrial applications. Its heavy-duty construction and sophisticated design makes it durable and highly efficient. The air blower is used in diverse industries specially cement, construction, processing and others. The technician records vibration signatures at regular maintenance intervals and the signatures 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.

5.1. Mathematical Analysis

$$\text{The dominant frequency } (f) = (V * 19120) / D. \qquad (4)$$

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 air blower 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

5.2. ***ANN – GA****: Analysis and Results*

The system adapts Artificial Neural Network for the analysis of Vibrations generated by the air blower (APPENDIX 1). 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 7 illustrates the process of the three layer neural network with three inputs and one output. Training the neural network has been done by using a procedure based on GA. The GA that was used in this study consists of 5000 generations and 100 individuals.

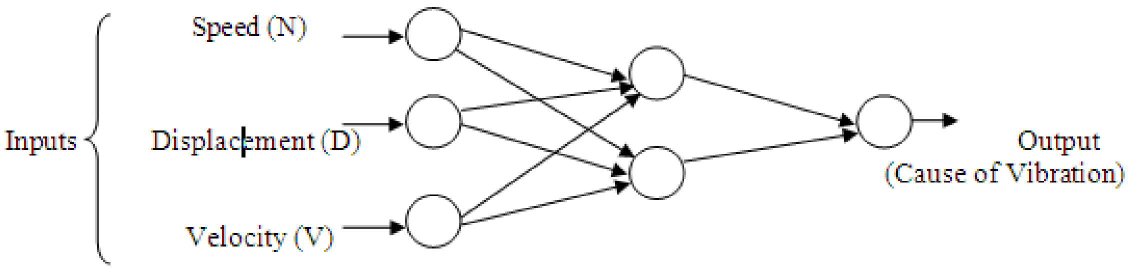

Figure 7: BPNN for an AIRBLOWER.

5.2.1. 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 air blower. Data is collected periodically from one of the AIR Blowers 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.

	Set 1	**Set 2**	**Set 3**
Speed(N)	4400	3600	4100
Velocity(V)	4	10	14
Displacement(D)	17	10	7
Mathematical Analysis	Unbalance	Bearing Problem	Unbalance
ICM Analysis	Unbalance	Bearing Problem	Unbalance

The Artificial Neural Networks based on BPNN and RBFNN algorithms based on Genetic Algorithm 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 by Genetic Algorithm.

No of Hidden Neurons	Training Set	Classification Accuracy	
		BPNN	**RBFNN**
2	5000	60	68
5	5000	71	74
8	5000	73	78
15	5000	85	90

Though the algorithms are applied to a single application based on air blowers they can be extended to other rotating machinery where we cannot rely on mathematical analysis which is error prone and time-consuming.

6. Conclusion

This paper presents an approach of designing and comparing two Artificial Neural Networks based on Back Propagation algorithm and Radial Basis Function which are optimized by genetic algorithm. Though the code is tested on industry samples for Air Blower Fault Detection, the concept with minor changes can be used for condition monitoring in other application.

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