

Fault Diagnosis Method for Mechanical Rotor Systems using ANN

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Abstract: Rotating machinery is an integral part in majority of industries. In rotating machineries, faults are inevitable due to the errors in manufacturing, errors while assembling different parts of the system and due to different operating conditions such as heat generation, looseness, wear, etc. Hence, rotating machinery needs to be monitored continuously for identifying the faults. Any defect in the parts of the rotating machinery will affect its vibration behavior and nature of this effect is different for different faults. Hence condition monitoring based on vibration measurements can be used to identify those defects qualitatively. The current study mainly concentrated on comparing the performances of Standalone Artificial Neural Network and Genetic Algorithm based ANN in fault diagnosis of rotating machineries and developing a Fault Detection Program (FDP) for identifying different fault conditions. Vibration signals corresponding to each fault conditions were recorded from an experimental set up by means of a Lab view data acquisition system. The statistical features of vibration signals were extracted using a feature extraction code and it was given as the input data to train the ANN. From the study, it is concluded that GA based ANN is a better choice for fault diagnosis compared to Standalone ANN.

Keywords: Artificial neural network, Genetic algorithm, Fault diagnosis, Fault Detection Program.

1. Introduction

Machine fault diagnosis is a field of mechanical engineering concerned with identifying faults arising in the parts of machineries. It is a vital process in any industry, because it avoids the failures in the machinery. Failures of machineries can be very critical since it leads to machinery damage, production losses and personnel injury. The faults arising in machines are often due to damages and failures in the components of the rotating system. Fault diagnosis is an important process in preventive maintenance of rotating system, which avoids serious damage if defects occur during operation condition. So it is necessary to detect the faults as early as possible to avoid the malfunctioning of machinery.

Vibration and acoustic analysis, spectrum method, cepstrum method, orbit method and wavelet method are some of the methods available in fault identification. These methods are found to be very practical and effective in fault identification if single fault exists in the machinery. When multiple faults occur it is very difficult to identify the faults by these methods. So, the multi-fault diagnosis is still a big challenge in monitoring and maintenance of rotating machinery. Reliability in the detection is an important criterion for the success of a condition monitoring system. Developing a method for identifying faults more accurately than that available at present is a big challenge to the researchers working in the field of condition monitoring. The Researchers are now working on the use of artificial neural networks (ANN) for fault diagnosis of machineries.

ANN can be used successfully to detect fault in machinery using statistical estimates of the vibration signal as input features. ANNs show promise for their application in condition monitoring. However, one of the main problems facing the use of ANNs is the determination of network

structure and size of input features of ANN used for this type of application. If too much input features are given, it will require a significant computational effort to calculate. To increase the accuracy of the classification and to increase the speed of classification, a feature selection process using genetic algorithms is used, to isolate those features, providing the most significant information for the neural network. Artificial neural network combined with Genetic algorithm is found to be very effective in the field of condition monitoring of rotating machineries.

In this paper, use of GA was studied for selection of the optimal input features for the neural network in diagnosing the faults in rotor systems. The performances of ANN with GA and without GA were compared and the performances obtained by changing the training function of ANN were also compared. A MATLAB Fault Diagnosis Program (FDP) was also created to diagnose faults in the rotating system accurately. It was found to be useful for the individuals in predicting the faults in rotor system, who do not know the basics of genetic algorithm and neural network.

2. Theory

A. Artificial Neural Network: An artificial neural network (ANN) can be defined as a mathematical or computational model that mimics the ability of the human brain in processing the information. The network structure consists of input nodes, nodes in hidden layers, output nodes, network connections, initial weight assignments and activation functions. In most cases, setting the correct structure of the network is a difficult task. The number of input nodes and output nodes are determined by the size of inputs and targets we are giving. When too many parameters are given to the network, it will lead to poor generalization, and when too few parameters are given it will result in

inadequate learning. Network learning is an important process since it determines suitability of network in solving the problems. Input patterns are exposed to the network and the network output is compared to the target values to calculate error, which is corrected in the next pass by adjusting the synaptic weights. Levenberg- Marquardt, Bayesian regulation and Gradient descent back propagation are some of the training functions. Fig1 shows a simple ANN and its constituents.

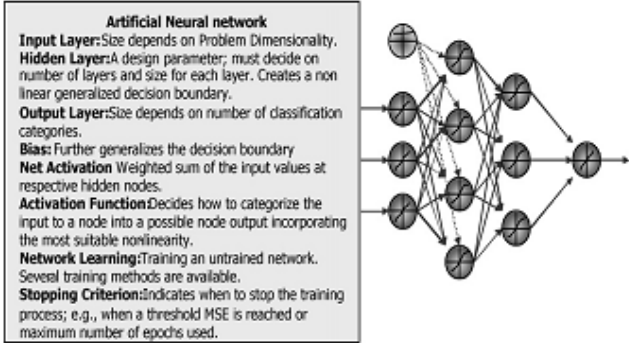
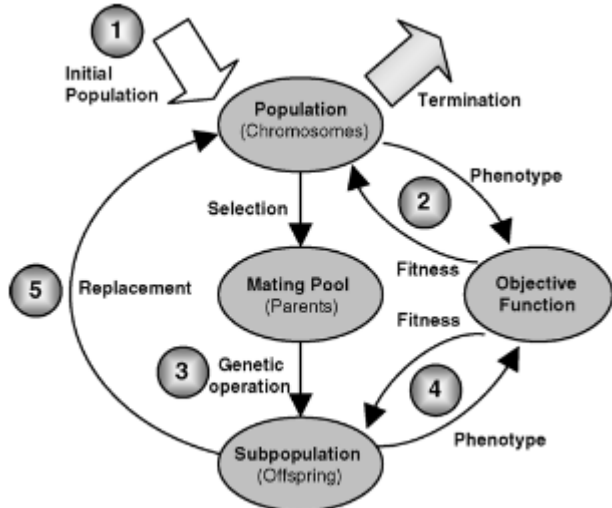


Figure 1: A general ANN with two hidden layers and its main components

B.Genetic Algorithm: Genetic Algorithm is an optimization procedure that is inspired by the processes observed in natural evolution. It is based on the laws of natural evolution and genetics. GA mainly consists of three processes: selection, genetic operation and replacement. The candidates of solution are grouped in a population and are called chromosomes in genetics. The fitness of these chromosomes is evaluated using an objective function. Fit parents are selected from the population to generate offspring by genetic operation such as cross over and mutation. Then the fitness of these offsprings is also evaluated and the earlier population is replaced by the new one. This cycle of evolution is repeated until the termination criterion is fulfilled. The best chromosome in the final population is the more superior solution to the problem. Fig 2 shows the basic genetic algorithm cycle.



Genetic Algorithm

- 1) Randomly generate an initial population $X(0) := (x_1, x_2, \dots, x_n)$ of chromosomes.
- 2) Compute the fitness $F(x_i)$ of each chromosome x_i in the current population $X(t)$.
- 3) Create new chromosomes $X_i(t+1)$ by mating the chromosomes (chosen parents) applying crossover and mutation.
- 4) Keep the desired number of fittest individuals to maintain the population size fixed.
- 5) $t := t+1$, if not (termination criteria), go to step 2, else return the best chromosome.

Figure 2: Genetic algorithm cycle and a simple top level description [9]

C. Combined GA and ANN

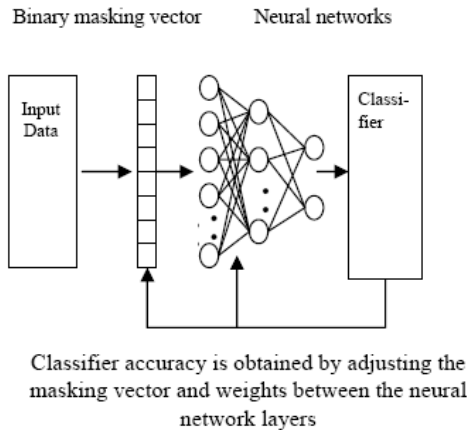


Figure 3: Schema of the proposed GA-based feature selection approach

The main statistical features extracted from the vibration signal were mean, maximum absolute amplitude, mean square value, RMS value, variance, kurtosis, skewness factor, crest factor and clearance factor. These features were given as the input to ANN. In order to incorporate GA into ANN, a binary vector was introduced which consists of binary digits 0 and 1 and the size of binary vector is same as that the number of input features corresponding to a vibration signal. A schema of GA based feature selection is shown in Fig 3. The modified feature set was used as the input set to ANN. The objective function of GA was to maximize the percentage of recognition and it will train the network until maximum percentage of recognition is obtained. The parameters of ANN and GA used for this study are listed in table 1 and table 2.

Table 1: Parameters of ANN

Parameter	Value
Network type	Feed forward back propagation
Adaption learning function	Gradient descent with momentum weight and bias learning function(LearnGdm)
Performance function	Mean Squared Error(MSE)
Number of hidden neurons	20

Table 2: Parameters of GA

Parameters	Value
Coding type	Binary coding
Population size	10
Selection operator	Tournament selection
Cross over operator	Arithmetic
Mutation operator	Flip bit
Selection rate	0.5
Mutation rate	0.15

$$\text{Percentage of recognition} = \frac{\text{Number of inputs correctly recognised}}{\text{Total number of inputs}} \times 100$$

3. Experimental Procedure

The simple rotor system consists of a single disc mounted on a shaft which is supported in ball bearings over a foundation. The system consists of a shaft carrying a centrally located steel disc weighing 0.75 kg. It is supported in identical rolling element bearings (type 6304 SKF ball bearings) at two ends and driven by a 12 volt, 0.25 HP, dc electric motor through a coupling. The speed of the motor is controlled by means of a variable d. C drive and vibration signals are recorded at ten levels of speeds starting from 200 to 1200rpm. The vibration signals for different fault conditions are recorded using a Lab view data acquisition system. Fig.4 shows the simple rotor system.



Figure 4: Experimental set up

The following faults were deliberately introduced in the system for generating training data:

- a) *Rotor with no fault:* There were no faults in the components of the system. The Rotor was perfectly balanced. The alignments and fittings were done properly.
- b) *Rotor with mass unbalance:* In order to create an unbalance, a mass of 0.05 kg was added at a radius of 20mm from the centre of the rotating disk.

- c) *Rotor with bearing fault:* Fault was created in a 6304 SKF ball bearing by crushing its inner race and removing some of the balls from it.
- d) *Rotor with misalignment:* Misalignment in the rotor was created by shifting the bearing block upward by about 3 mm, so that the axis of the two bearing blocks was out of alignment by about 3 mm.
- e) *Rotor with both mass unbalance and misalignment:* In this case both mass unbalance and misalignment were introduced simultaneously in the rig.
- f) *Rotor with both mass unbalance and bearing fault:* In this case both mass unbalance and bearing fault were introduced simultaneously in the rig.

4. Results and Discussions

Vibration data for six fault conditions were recorded from the rotor system using a Lab view data acquisition system and are shown in Fig 5.

The statistical features such as mean, maximum absolute value, variance, mean square value, RMS value, kurtosis, crest factor, clearance factor and skewness factor corresponding to each vibration signal were extracted using a feature extraction code. The feature extraction code was written in MATLAB. A set of statistical features of matrix size 9x80 were given as the input to ANN. A target matrix of size 7x80 was used to train the network along with the input set. The output generated by the network was compared with the target to calculate the percentage of recognition.

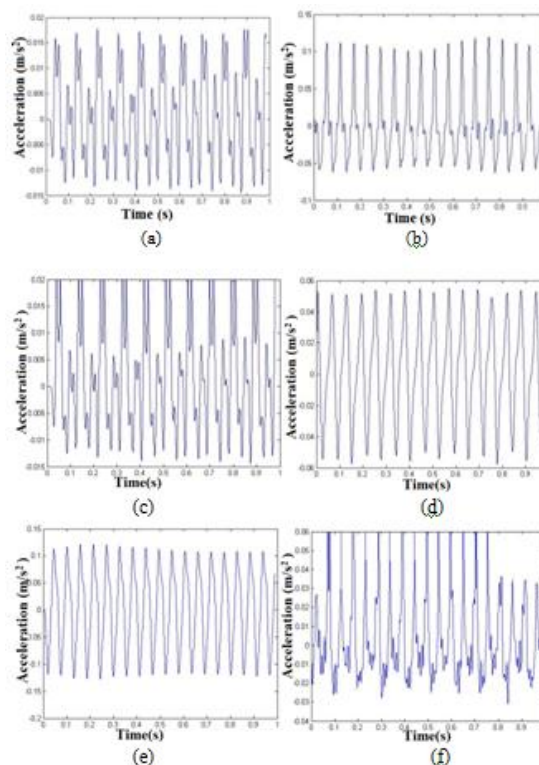


Figure 5: Vibration signal of rotor system having (a) no fault (b) bearing fault (c) misalignment (d) mass unbalance (e) both mass unbalance and bearing fault (f) both mass unbalance and misalignment at 200rpm.

When neural network was trained without feature selection using GA, the percentage of recognition obtained for different training functions of ANN is listed in the Table 3.

Table 3: Percentage of Recognition for different training function without GA

Training Function	Percentage of Recognition
Levenberg- Marquardt	91.255
Bayesian Regulation	84.269
Gradient descent back propagation	87.057

From the table 3, it is clear that when neural network was trained without Genetic algorithm, the percentage of recognition was below 92 percentages. Regression lines for different training functions of ANN, without GA are shown in Fig 6.

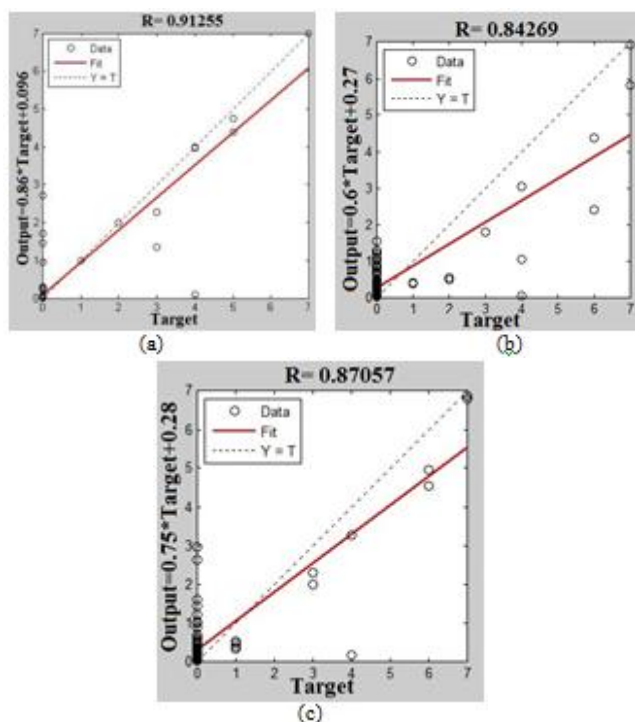


Figure 6: Regression lines for (a) Levenberg- Marquardt, (b) Bayesian Regulation, (c) Gradient descent back propagation (without GA)

In order to increase the percentage of recognition, Genetic algorithm was introduced with neural network. GA produced a population of binary vectors and each binary vector was multiplied with feature set. These modified feature set was given as the input to ANN and the network was trained until maximum percentage of recognition was obtained. Genetic algorithm selected mean, maximum absolute value and crests factors as the significant features for the neural network and found that these three features were the optimal features.

The percentage of recognition obtained for different training functions of ANN with GA is listed in the Table 4.

Table 4: Percentage of Recognition for different training function with GA

Training Function	Percentage of Recognition
Levenberg- Marquardt	100
Bayesian Regulation	100
Gradient descent back propagation	99.569

From the table 4, it is clear that when GA was used to select optimum input features for ANN, the recognition efficiency increased to above 99 percentages. For Levenberg-Marquardt and Bayesian Regulation training functions, the percentage of recognition was 100. Regression lines for different training functions of ANN, with GA are shown in Fig 7.

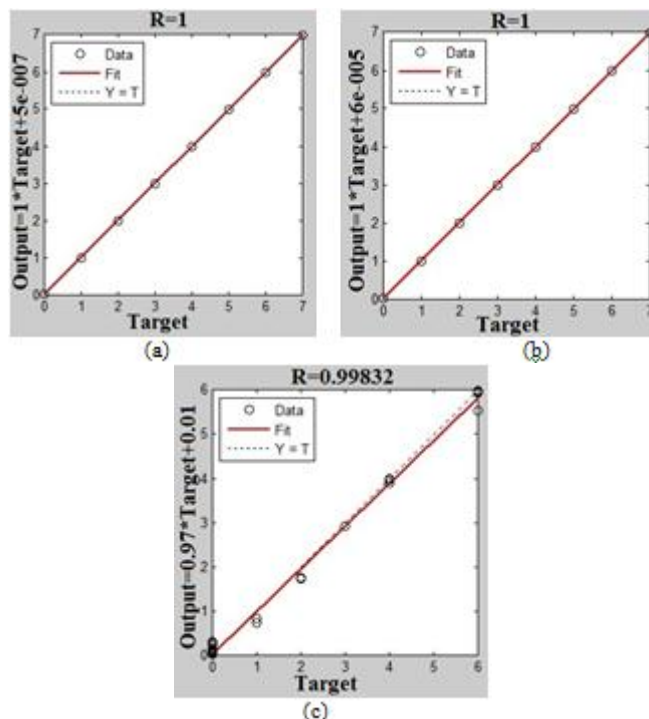


Figure 7: Regression lines for (a) Levenberg- Marquardt, (b) Bayesian Regulation, (c) Gradient descent back propagation (with GA)

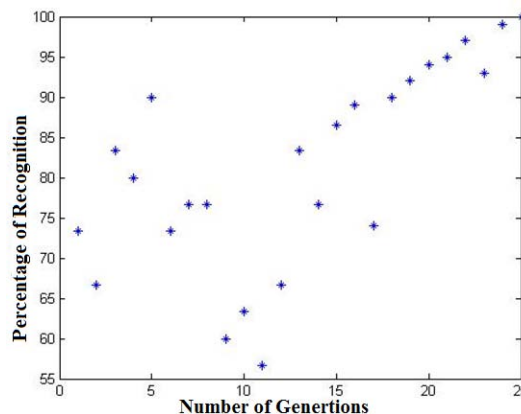


Figure 8: Percentage of recognition versus number of generations for Levenberg- Marquardt

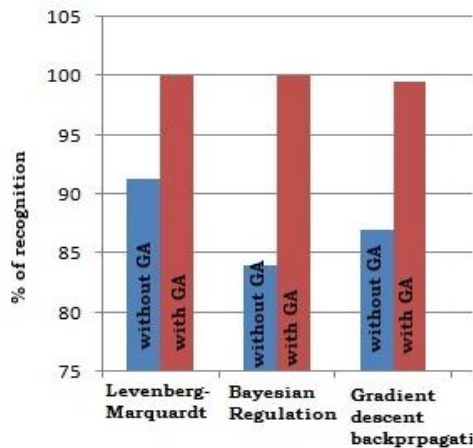


Figure 9: Comparison of the performances of neural network with and w/o GA

The percentage of recognition was converged to 100 for the 25th generation of genetic algorithm cycle and is shown in Fig 8. From the Fig 9, it is clear that the performance of neural network with GA is better compared to that without GA. This is due to the optimal selection of input features by Genetic algorithm.

Using the neural network having a maximum percentage of recognition, a MATLAB Fault diagnosis program (FDP) was created. It has been found that out of nine features, only five, ie Mean, Maximum absolute amplitude, RMS, Variance and Clearance factor are the optimal input features for neural network. Thus using the program of GA based ANN; a MATLAB Fault Diagnosis Program was created. The FDP was tested with 20 test inputs and it was found that FDP was accurately identifying the fault in the rotor system. The Fig 10 shows the execution of the Fault diagnosis Program (FDP) for the rotor system.

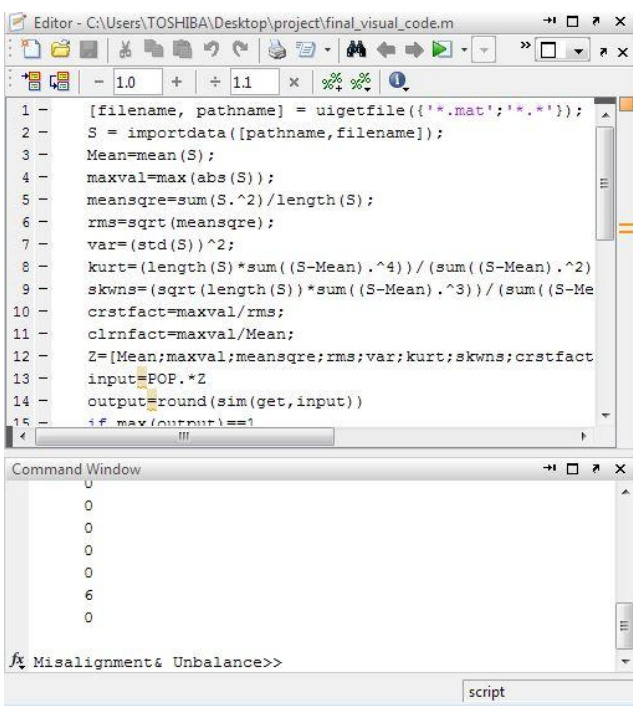


Figure 10: FDP executes and correctly diagnoses the type of fault associated with the vibration data

5. Conclusions

Genetic Algorithm is a suitable optimization technique for selecting optimal input features for neural network. The statistical features such as Mean, Maximum absolute amplitude, RMS, Variance and Clearance factor are the optimal input features for neural network in the case of rotating systems. For Standalone ANN, a maximum percentage of recognition of 91.25 is obtained for the rotor system. For GA based ANN, a maximum percentage of recognition of 100 is obtained for the rotor system. On comparing the performances of Standalone ANN and GA based ANN, it is concluded that GA based ANN is most effective in fault diagnosis. A MATLAB Fault Diagnosing Program (FDP), created on the basis of a GA based neural network is found to be very useful in the fault diagnosis of rotating system. It will be helpful for the persons, who do not know the basics of ANN, GA and programming, in diagnosing fault.

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