Machine faults diagnosis using Non-Traditional Optimization Technique

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***Abstract*— In the field of engineering application machines are subjected to vibration. It is essential to suggest a modeling method to predict and analyze the faults occurring due to vibration in machine. In the present work the faults are responsible for vibrations occurring in ball bearing used in machines. This fault causes personal injury, time losses. We are going to analyze location of bearing faults and classification of faults with the help of experimental work and advance optimization tools (non-traditional optimization technique) e.g. genetic algorithm, neural network etc. This study focuses on evaluation and prediction of faults on various bearing elements. We have developed a standardize model for the detecting faults of bearing elements which will be applicable for variety of bearings.**

For detection of faults in bearing, FFT analyzer is used to collect rough vibration signal from single deep groove ball bearing at condition 1000 rpm and constant load. Subset of 16 inputs is selected from set of 40 by using MATLAB 13. ANN architecture is applied to classify the features extracted from bearing data. This study also focuses on optimization of ANN parameters and reduces number of trial and error.

***Keywords*— Bearing faults, FFT Technique, ANN Structure, Optimization**

I. INTRODUCTION

In the field of engineering application there is close relationship of machine motor system and any bearing assembly. In any modern rotating machinery system bearings f are important part and faults in bearing easily affect the performance of machine. This bearing element is subjected to faults. We are going analyze faults location in bearing elements and classification of faults with the help of experimental work and advance optimization tools.(non-traditional optimization technique) e.g. neural network, genetic algorithm etc. Bearing faults causes personal injury, financial and time losses if defect is not detected in time to time [1]. Inaccurate installation, improper lubrication, or material fatigue may cause some localized defects of bearing, which cause an impulsive vibration whenever the bearing component passes over the defect. There are different methods are available to detect faults in bearing may be roughly classified as vibration, acoustic and temperature measurement in these vibration measurements in time and frequency domains acoustic emission technique are usual methods. The measurements of resonant response of an accelerometer, excited by faulty components were studied for diagnostics. Time-frequency domain techniques including both time and frequency data enable capturing transient features such as pulse signals. FFT effectively used in the spectrum analysis of different vibration data. Various Ann methods are used for diagnostics of bearing faults. The most used ANN method is back propagation, feed forward. For large system it becomes complicated. If the number of parameters is high and convergence to local minima is serious concern, then Genetic algorithm is become prominent. GA has proven to best function with ANN in determining the compact architecture improving the estimation performance.

The study here aims to detect the potential of vibration monitoring, feature extraction accompanied with FFT methods ANN architecture optimized by GA researchers hold that step is used to classify the features extracted from fault diagnosis of bearing. GA is demonstrated for selection of smaller MSE, number of hidden layer and number of neurons in the hidden layers in ANN system.

II. LITERATURE REVIEW

Many researchers have addressed the effect of faults in bearing parameters, and detection of different method like wavelet analysis, empirical mode decomposition. Muhammet Unal et.al. [1], reported the work on feature extraction and envelope analysis by using FFT and Hilbert Transform (HT). HT is used to obtain local energy of each frequency and then using optimized ANN to classification of faults for roller bearing. L.B.Jack [2], presented the method of detecting faults in machine using statistical estimation of vibration signal which is given to input feature. By using high and low pass filtering statistical frequency data obtained. Then apply normalization to spectral data which is obtained from FFT. Yongxiang Zhang [3] presented the method based on the combination of genetic algorithm and kurtosis. Bo Li [4] presented the method the sensors collect time domain signals. The FFT is used to convert the time domain signals into frequency domain signals. And neural network and kurtosis are applied to given frequency data and obtain network which detecting faults with improved results. Adam Docekal [5] presented the method to detect faults in rolling bearing using resonant modes and niching genetic algorithm. For adaptive selection of frequency bands in which presence of resonant modes of rolling bearing which is tapered roller bearing with some faults. To detect this faults niching genetic algorithm is used. GA used to construct band-pass filters with adaptive parameter in which one property is maximized. GA provides optimization with maximize filtered signal and resonant modes. Yaguo Lei [6] presented the method of detecting faults in rolling element of bearing using empirical mode decomposition with neuro-fuzzy inference system. Feature extraction, EMD, ANFISs are three steps performed to detecting faults in bearing. Peter W.Tse [7] presented the method to detect faults in bearing using wavelet transform and again genetic algorithm used to increase efficiency of wavelet transform. Chkraborty [8], presented the method to detect faults occurring in bearing with fuzzy logic and genetic algorithm. In this feature selection is done with fuzzy logic. Fuzzy is having remarkable ability of handling real life problem forming characteristics.

III. PROPOSED WORK

From the above literature review the following research issues are identified.

1. It is found that fewer researchers have focused on the single point and multi point defects in the races of the bearing.
2. Several researches have reported success in observing the defect frequencies in vibration spectra measured from a defective bearing
3. There are fewer studies on vibration-based data acquisition methods to determine the effect on bearing when the defect is present on races of bearing.
4. Defects in deep grove ball bearing in their early stage may results in higher noise and vibrations and finally leading to failure of bearing system causes regular maintenance, machinery breakdown and significant economic losses.
5. Appropriate condition-based (vibration) diagnosis of transient behavior of deep groove ball bearing, it is known the defective component and effect of number, types and orientation of defects in rolling elements.

IV OBJECTIVE OF STUDY

1. To analyze vibration response of rolling element of bearing for deep groove ball bearing.

2. To conduct experimental test with deep groove ball bearing, FFT analyser ,EDM (electric discharge machine)

3. To analyze the frequency domain when single point in the races of the deep groove ball bearing by using frequency spectrum.
4. To analyze the effect of change in dimensions of single point defects in races of deep groove ball bearing using frequency spectrum.
5. To analyze the effect of defect on the deep groove ball bearing using ANN.
6. To analyze ANN and using GA to obtain best optimized results and compare it with ANN.

V.METHODLOGY

In the present investigation the bearing vibration create noise and degrade in the performance of any rotating machinery. In mechanical rotating devices bearing failure is of paramount importance which needs immediate attention to reduce the faults. The faults in bearing parameters were recognized by way of FFT analyzer. The results obtained were further analyzed by using Artificial neural network with 16 input set which extracted by data obtained from FFT. We are taking single deep groove ball bearing for our study purpose In this study bearing geometry parameters were used for obtained defect frequency. Equations and characteristics are shown in Table I.[1]

Table 1
Characteristics of test bearing

Parameter	VALUE
Inner race defect frequency	$N/2*f_r*(1+R_b/d_m)$
Outer race defect frequency	$N/2*f_r*(1-R_b/d_m)$
Ball spin frequency	$d_m/2\ R_b*\ f_r*(R_b/d_m)^{\wedge 2}$
External diameter (D)	42mm
Diameter of ball (R_b)	6.35mm
Pitch circle diameter	31mm
Number of balls	9
Bore diameter	20

Using above data inner race defect frequency is 126 Hz, the frequency of ORD settles at 26 Hz and ball spin frequency is 11 Hz. An experimental set up used in this project is shown in figure 1. Shaft is supported by two test bearings at its end with AC motor and to change speed one electrical drive is used. Acceleration sensor is used to pick up the acceleration .for good and faulty bearing signals were obtained for different rpm. One end of sensor is mounted on bearing housing and other end is connected to FFT.

A. Instrumentation

Vibration signals from single deep groove ball bearing was acquired with accelerometer and time domain, frequency domain acquired with radial and axial direction with various speed. Vibration signals analyzed with FFT. On single deep groove ball bearings single point defect is created on inner raceway and outer raceway by using EDM electric discharge machining. Vibration data from the bearing is collected at different speed like 1000,2000,3000,4000 rpm. The load on bearing was considered constant on good bearing. Amplitude of the vibration is changes by changing operating parameter. In figure 1 shows experimental set up.

B. ANN PARAMETERS

Artificial neural networks are systems that simulate the microstructure (neurons) of a biological nervous system. A simple process element of the ANN is shown in Figure2.The network has three layers; the input, hidden, and output layers. The input and output layers are defined as inputs and outputs [2]

FIGURE 1: EXPERIMENTAL SET UP

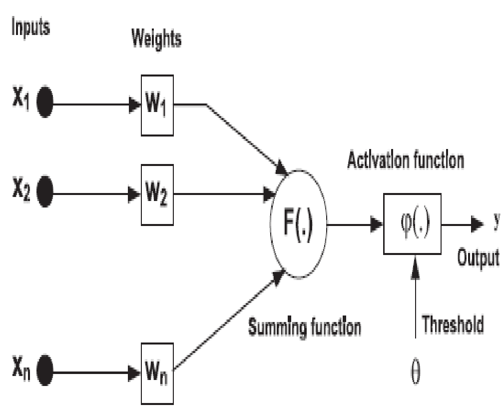

Figure 2: mathematical model of neural network

The network performance is obtained by using the test dataset. The quality of the prediction can be evaluated by the mean square error (MSE) of the predicted values from the real measured data. Smaller the MSE of the test dataset higher is the predictive quality. e is MSE t is target output and o is desired output.

$$e = \frac{1}{2}\sum_{i=1}^{q}\left(t^{i} - o^{i}\right)^{2}$$

The developed ANN architecture is computed in MATLAB 13 with 16 inputs sets. The output is one variable value. The output value is in binary form such as 1, 0 which indicates classification of the faults. To increase performance of ANN by trial and error method, with changing neuron value, hidden layers. We have to determine optimized value of MSE. To obtain this objective, we have to apply trial and error method to ANN. By changing number of neurons, hidden layer we obtained less value of MSE. Each number neuron does not affect on output directly, therefore neuron are selected individually. Each and every instant a check should be made whether a different output occurs or not.

Steps to evaluate ANN in the experimental and predicted value of ANN in Matlab tool [17]:

1. Scripts assume that the input and vectors are already loaded into workspace. If the data are not loaded u can load them as follows:
2. Nntool > import > load house dataset; inputs = houseinput;Targets =house target;
3. Create network; the default network for function for fitting problem, fitnet ,is feed forward network with the default tan-sigmoid transfer function is present in the hidden layer and linear transfer function in the output layer. The network has one output neuron, because there is only one target value associated with each input vector.
4. Set up the division of data. With these settings, the Input vectors and target vectors will be randomly divided, with 80% used for training, 20% for validation and 20% for testing.
5. Train the network. The network uses the default algorithm (trainlm) for training. For problems in which Levenberg- Marquardt does not produce as accurate results as desired, or for large data problems, consider setting the network training function to Bayesian Regularization (trainbr) or Scaled Conjugate Gradient (trainscg), respectively.
6. Stop Training If you click Performance in the training window, a plot of the training errors, validation errors, and test errors appears.

In this study ANN is used to classify the faults of bearing.

V. MACHINING PERFORMANCE MEASURE

The present study, faults in bearing were the output factor affecting the result of machining process by varying load, speed. In each and every machine rolling elements of bearing is running at some speed, when faults are introduced in bearing the vibration spectrum are changed. The frequencies of vibration occurring from faults are called bearing defect frequencies which is calculated by using geometry of bearing and shown in Table I. peak frequencies are occurring in spectrum because of change in vibration. Model presented by jack [2]; predicted peaks are presented in frequency spectrum at defect frequencies. Defect frequencies are calculated by following equation. [2] .

Ball pass frequency of inner race (IRD):-

IRD = $N/2*f_r*(1+R_b/d_m)$ =123.33Hz……………..(1)

Ball pass frequency of outer race (ORD):-

ORD = $N/2*f_r*(1-R_b/d_m)$ =26.66 Hz…………..(2)

Ball spin frequency (BSF):-

BSF = $d_m/2\ R_b*\ f_r*(R_b/d_m)^{\wedge 2}$ = 5.374 Hz………(3)

Theoretical calculation at different harmonics is done by using above equation. Firstly vibration signal collected in the form of rough signal time domain FFT convert it in frequency domain signal. Amplitude of each signals are considered for further analysis. Feature extracted from this signal by creating program in Matlab.

VI. RESULTS AND DISCUSSION

In figure 3 and 4 shows acceleration spectrum for good bearing and faulty bearing.

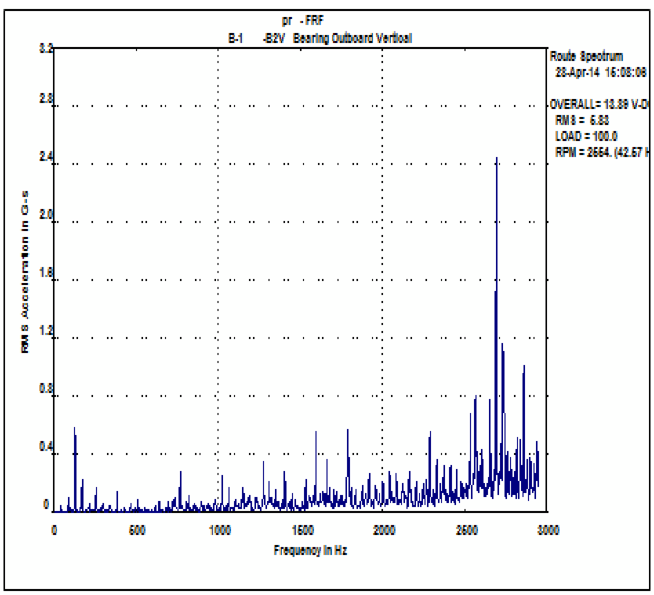

Figure 3: Spectrum for good bearing at different speed.

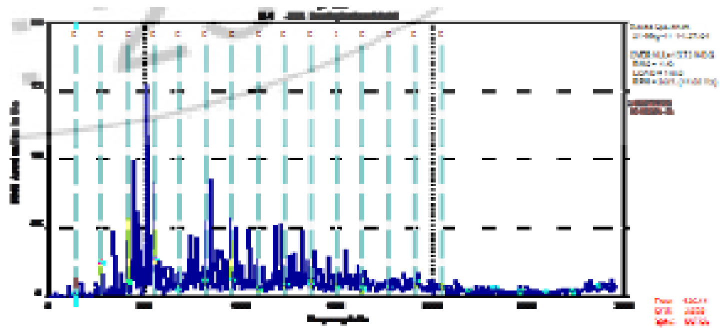

Figure 4: Spectrum for defective bearing

Figure 3 and figure 4 shows frequency waveform for good bearing and defective bearing It is observed that the spectrum clearly shows the presence of fault on the inner race and the balls. The theoretical defect frequency and spectrum obtained from FFT almost matches but in spectrum unwanted signals are also presented so we need to do feature extraction. From MATLAB program we can obtain input vectors for ANN.

The table II shows feature extracted from spectrum for shaft frequency and it's harmonics for good bearing like this there are for 10 signals we obtained. Training data were used to update ANN models weighting coefficients and threshold values. After training process a new data set was fed to ANN input to quantify the level of prediction of target outputs. The experiments were repeated three times to provide a better, input variable spacing for classification of bearing faults.

Table II
Frequency signals for good bearing

Nature	Feature	Value
Good bearing	F1	0.00456
	F2	0.002592
	F3	0.002477
	F4	0.001915
	F5	0.001529
	F6	0.000302
	F7	0.000579
	F8	0.005255
	F9	0.000289
	F10	0.000573
	F11	0.000265
	F12	0.000718
	F13	1.07E-05
	F14	0.000508
	F15	0.000774
	F16	0.000371

Table III
Signals for inner race defect bearing

nature	feature	value
	F1	0.001396
	F2	0.001795

Inner race defect	F3	0.012746
	F4	0.00552
	F5	0.002147
	F6	0.006051
	F7	0.016292
	F8	0.001555
	F9	0.004801
	F10	0.000734
	F11	0.00334
	F12	0.007689
	F13	0.010076
	F14	1.06e-05
	F15	0.000673
	F16	0.001263

Table III shows inner race defect frequency signals and it's harmonics for first signal like this we obtained for 10 signals. Frequency spectrum of vibration data does not include characteristics feature of the faults. Instead. FFT methods are used to obtain local energy of each instantaneous frequency for extraction of the features. the frequency components that characterize the faults are found in the form of peaks and amplitudes with relatively large harmonics compared to other fault-free ,IRD, ORD, and BSF vibration signals of specific frequency components and corresponding harmonics after the feature extraction.

The selected frequencies and amplitude input to the ANN for feature extraction of classification are listed in the above table. Several ANN models with different number of hidden layers and neurons were generated for different classification purposes.

Table IV
Signals for outer race defective bearing

nature	feature	value
outer race defect	F1	0.003726
	F2	0.000888
	F3	0.000824
	F4	0.001168
	F5	0.002436
	F6	0.003728
	F7	0.000899
	F8	0.00207
	F9	0.00046
	F10	0.000531
	F11	0.001098
	F12	0.009552
	F13	1.68E-05
	F14	0.00064
	F15	0.001024
	F16	0.000262

Table IV shows outer race defect frequencies for bearing for its shaft frequency and three harmonics. Like this for 10 signals we obtained from feature extraction by using FFT.

Table v
Signals for ball spin frequencies

nature	feature	value
Ball defect defect	F1	0.006328
	F2	0.001681
	F3	0.000712
	F4	0.000418
	F5	0.002413
	F6	0.001585
	F7	0.01423
	F8	0.001069
	F9	0.000788
	F10	0.000173
	F11	0.000283
	F12	0.007382
	F13	2.68E -05
	F14	0.000625
	F15	0.000815
	F16	0.000171

Table V shows ball spin frequency for 16 features which are shaft frequency and its harmonics for defect ball bearing. Like this for 10 signals we obtained feature. Input matrix for ANN is become 16*40 and target vector represented in the form of binary digit. Matrix for target vector is 4*40. Table below shows target value used in ANN. ANN based methods are applied to a large number of problems due to its sufficiency of handling nonlinear nature of system. ANN applications utilize simple multi-layer perceptron network training based on feed forward algorithm. It map the relationship between input and output and store this relationship into set of intrinsic parameter. Typical MLP network is embedded in layers of the neurons where each neuron in layer computes the sum of its input variable and passes the sum through an activation function.

Table vi
Target value

TYPE	BINARY FORM
GOOD	1000
IRD	0100
ORD	0010
BSF	0001

By using above value input and target data loaded in ANN tool and obtain ANN architecture. by changing ANN parameter obtained significant ANN structure which easily detect faults in bearing element. Hidden layer is varying in 1 to 3 and number of neurons in 1 to 30 [1].shown in figure below.

Trained network using above given data and obtained result. In ANN weights and threshold are randomly selected, thus architecture providing similar layer and neuron for different performance values after training. So it results in different classification value during evolution of fitness value. So optimization of ANN is done.

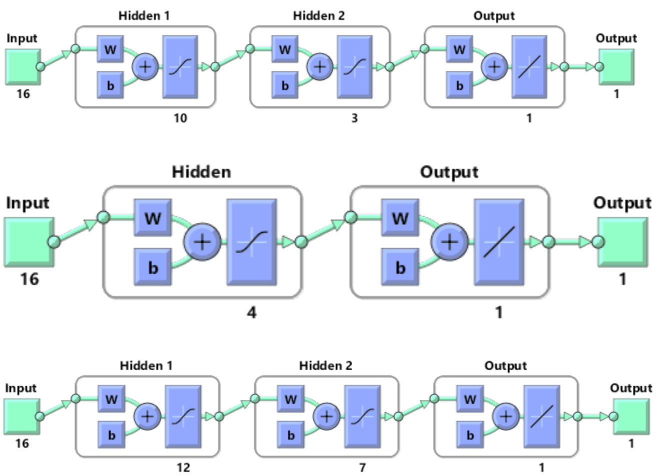

figure 5: ANN architecture for different hidden layers and neurons.

Figure 5 ANN models were obtained by MSE determining a correlation value between the target and ANN outputs. The models represent fast running network architecture with minimum MSE error and an appropriate correlation value. In the hidden layer of ANN models, hyperbolic tangent function was selected as the activation, providing an output varying between -1 to 1.A linear activation function was also selected for output layer.

Figure below shows correlation between coefficients of ANN desired value and actual value for all cases. Overlapping obtained output and outputs given to ANN indicate ANN model classifies different faults.

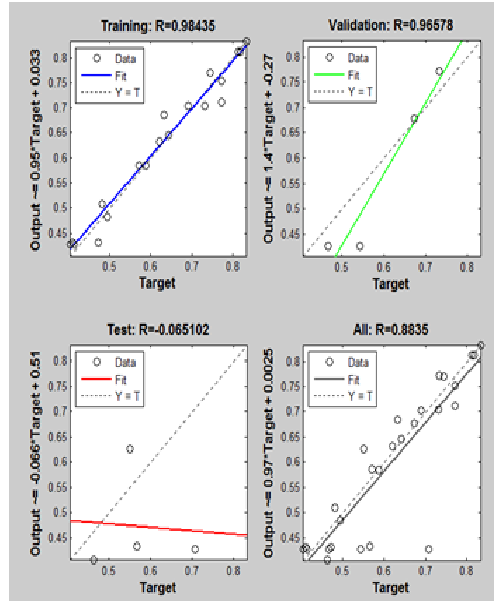

Figure 6: correlation between ANN output and target

A. OTIMIZATION

ANN parameters are optimized by using (GA) genetic algorithm. The objective of GA is to control the value of mean square error, and simplifies the ANN structure. Fitness function is shown by

$$F= MSE+(1- C)^* (w/wn)^*10^{-5} + C^*(n/nn)^*10^{-5}$$

Where,

C = randomly selected weight which is 0.8

w= interconnected weight value between input and output, hidden layer.

Wn = maximum number of all interconnection

n = neuron

nn= maximum number of neuron which is 30

10^-5= weight constant.

GA parameters are real coding, population size are 10, tournament selection operator, crossover operator is scattered, probability 80% mutation operator is Adaptive feasible, elite count is 2, rank based scaling. Limits are defined each and every parameter. The performance of GA-ANN models, were evaluated in terms of MSE and correlation coefficient. ANN models illustrated in below figure were obtained after the GA optimization; also their parameters, training and test performance are comparatively given in table VI.

In GA parameter F is fitness value. Number of hidden layer is limited between 1 and 3 and neurons are limited in between 1 and 30.

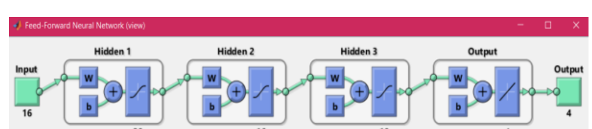

Figure 7: ANN-GA Based model

Figure 7 shows GA based ANN model in which 3 hidden layer, 30 neurons in first hidden layer,16 in second and 10 in third hidden layer. In output layer, 4 neurons. In which in hidden layer hyperbolic tangent function was selected as activation and linear function used in output layer.

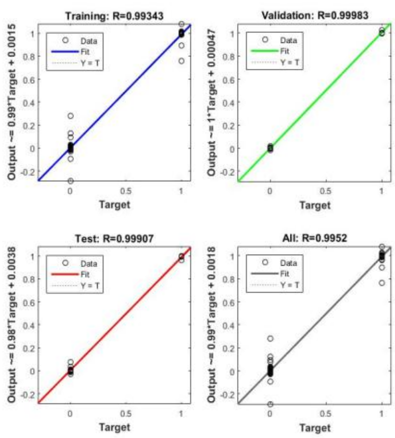

Figure 8: correlation between GA-based ANN models

Figure 8 shows better regression value than ANN value performance rating for classification of different faults with GA is shown in following table.

Table VI
Performance rating for ga-based ann model

CLASS	CORRELATION VALUE TRAINING	TEST
GOOD	0.98345	0.9657
WITH ALL FAULTS	0.065102	0.8835
GOOD WITH GA	0.99343	0.9989
ALL FAULTS WITH GA	0.9907	0.9957

In following table IRD,ORD and BSF faults can be easily distinguished where ANN model for fault location includes one hidden layer and in other two and from this table ,output value and target values indicate that ANN models classifies the faults successfully. Genetic algorithm providing ,an optimal skill and fast reacting network architecture with improved classification results.

Table VII
GA-ANN performance value

faults	Hidden laayer	Neuron number	Mse training	Mse test
good	3	10	0	0
ird	2	4	5.2e^-5	5.6e^-5
ord	2	12	7.6e^-5	1.2e^-5
bsf	1	15	1.1e^-5	3.3e^-5

VII.CONCLUSION

In present study, discussed different faults occurring in elements of bearing in rotating machinery, Signal processing provide feature extraction which is used to detect faults in element. Based on extracted information ANN is used to classify different faults.

- ❖ The results of 16 experiments were splits as 80% for training and 20% for testing. It provides 98% success. Testing and test performance are comparatively given in above table. IRD, ORD, BSF faults can be easily distinguished where ANN models including 1 to 3 hidden layer,1 to 30 neurons.
- ❖ Signal processing provide feature extraction which is used as input in ANN. Based on extracted information ANN is used to classify different faults.
- ❖ Overlapping output and target value in GA-ANN indicate that the model classifies the faults successfully.
- ❖ The correlation rate is 0.9957 for validation and mean square error 10^-5 . Indicate ANN predicted value and estimated value are close.

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