Bearing Fault Diagnosis Using Fuzzy Inference Optimized by Neural Network and Genetic Algorithm

Hong-Hee Lee†, Ngoc-Tu Nguyen* and Jeong-Min Kwon**

Abstract – The bearing diagnostics method is presented in this paper using fuzzy inference based on vibration data. Both time-domain and frequency-domain features are used as input data for bearing fault detection. The Adaptive Network based Fuzzy Inference System (ANFIS) and Genetic Algorithm (GA) have been proposed to select the fuzzy model input and output parameters. Training results give the optimized fuzzy inference system for bearing diagnosis based on measured vibration data. The result is also tested with other sets of bearing data to illustrate the reliability of the chosen model.

Keywords: Bearing diagnosis, Fuzzy, Genetic algorithm, Neural network, Vibration

1. Introduction

Bearing damages are very common faults of rotating electrical machines; numerous works have been developed to identify the bearing conditions. In recent years, bearing diagnostics technology continues to grow rapidly; most of which are based on the artificial neural network (ANN), fuzzy technology, or expert system using vibration data. The time-domain vibration signal is useful to the extent of determining the overall vibration level. For many cases, the time signal is sufficient to diagnose the health of a machine. Sometimes, time signals may not exactly indicate the defect. In that case, the frequency spectrum from a Fourier analysis is used to extract frequency-domain features of measured vibration signals. Time-domain features have been extracted for fault diagnosis of rolling element bearings as shown in [1] and [3]. In [6], one research based on frequency features of the vibration signal is presented. The work in [6] used fuzzy technique with linguistic variables that describe the human way to determine bearing defects. A disadvantage of this technique appears to choose the suitable configuration of fuzzy model considering the effect of measured data. Some recently proposed ideas are to use ANN and genetic algorithm (GA) to take advantages from experiment data. Samanta and Al-Balushi [3] described the ANN approaches to diagnose the ball bearing conditions using time-domain features, or combined with GA in [1]. Lou and Loparo [2] applied an adaptive neural-fuzzy inference system (ANFIS) based on wavelet transform for the diagnosis of localized defects in ball bearings, etc. ANN and ANFIS are also demonstrated as effective tools for fault diagnosis of rotating machines in [4-6], [13].

The work herein suggests a method that uses fuzzy logic for diagnosing the bearing conditions and obtains the optimal configuration for the fuzzy model. Fuzzy logic is a way of processing data by allowing partial set membership rather than crisp set membership or non-membership, and uses simple rule-based if-then to solve the problem rather than attempting to model a system mathematically. The system is designed using an ANFIS, which is a powerful hybridized system within the ANN and fuzzy system [7]. Parameters that determine the shape of membership functions are learnt by the ANN algorithm while model parameters such as membership function types, number of membership functions, and membership function parameters are optimized by genetic algorithm. The method combined the advantages of fuzzy and ANN techniques, which allow using linguistic variables as the inputs of the system, and are suitable when dealing with measured data.

Vibration data of the induction motor with and without bearing faults is used to train the ANFIS. In order to obtain the data features, an accelerometer sensor is installed on the induction motor to measure vibration signals of normal and defective bearings. Both time-domain and frequency-domain features are considered, that are amplitude of time signal and amplitude of basic bearing frequencies. Training epochs are also considered to get a suitable training averaging error when training the ANFIS.

† Corresponding Author: School of Electrical Engineering, University of Ulsan, Ulsan, Korea (hhlee@mail.ulsan.ac.kr)
* School of Electrical Engineering, University of Ulsan, Ulsan, Korea (nntu@hcmut.edu.vn)
** School of Electrical Engineering, University of Ulsan, Ulsan, Korea (ruee006@mail.ulsan.ac.kr)
Received 21 October, 2006 ; Accepted 21 April, 2007

2. Adaptive Network-based Fuzzy Inference System (ANFIS) and Genetic Algorithm (GA)

2.1 ANFIS

ANFIS is a neuro-fuzzy system whose structure is a multi-layer ANN. It embeds fuzzy rules with the ANN and uses a backpropagation-like algorithm to fine-tune the parameters of the single-output, Sugeno-type fuzzy inference system. The learning algorithm combines least-squares and back-propagation (BP) gradient descent methods. Figure 1 illustrates a simple example of an ANFIS. There are two rules for this example:

Rule 1: If X is A1 and Y is B1, then $T1 = p1X + q1Y + r1$

Rule 2: If X is A2 and Y is B2, then $T2 = p2X + q2Y + r2$

Layer 1, called fuzzification, is used to fuzzify the values of the input variables. The parameters in this layer are generally referred to as premise parameters. These premise parameters are fine-tuned by the backpropagation-like algorithm. Layer 2 is fuzzy AND which performs a fuzzy AND operation at the nodes. Layer 3 is normalization and layer 4 is fuzzy inference, which estimates the rule's output. Each rule's output is a crisp value, and its parameters (pi, qi, and ri) are adjusted during the phase of parameter identification. These parameters are referred to as the consequent parameters. Finally, layer 5, called defuzzification layer, calculates the sum of the outputs of all the rules and produces a crisp output.

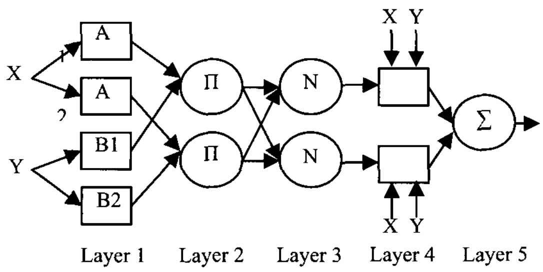


Fig. 1. An adaptive network-based fuzzy inference system

The learning operation of ANFIS includes 2 steps: in the first step, the premise parameters are assumed to be fixed and the optimal consequent parameters are estimated by an iterative least mean square procedure using training data. The second step, the consequent parameters are assumed to be fixed and the premise parameters are modified using back-propagation algorithm.

2.2 Genetic algorithm (GA)

GA algorithm is used to give the solution by simulating the evolutionary processes of *survival of the fittest,* which ensures that the best members of population are retained. The algorithm begins with a set of solutions (chromosomes) called population. Solutions from one population are reproduced to create a new generation of population. Mutations are also occurred randomly in each population.

The GA algorithm is as follows:

- Generate an initial population of random chromosomes.
- Calculate fitness of each chromosome.
- Reproduce next generation by selecting pairs of parents. During reproduction, crossover of the genes and random mutation in some of the children are occurred.
- The reproduction continues until the best solution is created.

Randomness plays a central role in the GA process; many random procedures are used during execution of GA algorithm.

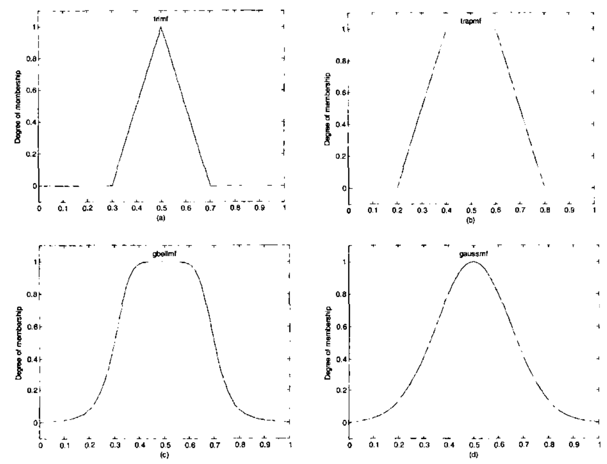


Fig. 2. MF types are used in GA,
(a) trimf, (b) trapmf, (c) gbellmf, (d) gaussmf

In the present work, the GA algorithm is used to choose the local optimal number of membership functions as well as the type of them. The fitness function of GA is defined as the least mean square error of the ANFIS model. While ANFIS is applied for optimization of the premise parameters (input membership functions) and the consequent parameters (output membership function), GA algorithm will search for the best ANFIS configuration based on minimizing the least mean square error between the expected and real output of the network. In order to simplify the system, only 2 inputs are used: time signal amplitude to measure the severity of bearing defect and bearing frequency magnitudes to detect the problems. Only one output is utilized to indicate whether a bearing is good (0) or not (1). The set of possible input membership functions is *{trimf, trapmf, gbellmf, gaussmf}*, output membership function is *{constant (z=ci), linear* *(z=piX+qiY+ri)}*, the number of membership functions for each input is in range from 2 to 6.

3. Bearing Vibration Features

Vibration training data are processed in both time signal and FFT spectra. The maximum amplitude of time signal and the sum of bearing frequency amplitudes are preferred as input of the ANFIS model. Only one output is used to detect bearing conditions: normal or damage, corresponding to binary values 0 or 1. Bearing frequency amplitudes are calculated with a 5 Hz frequency band around them.

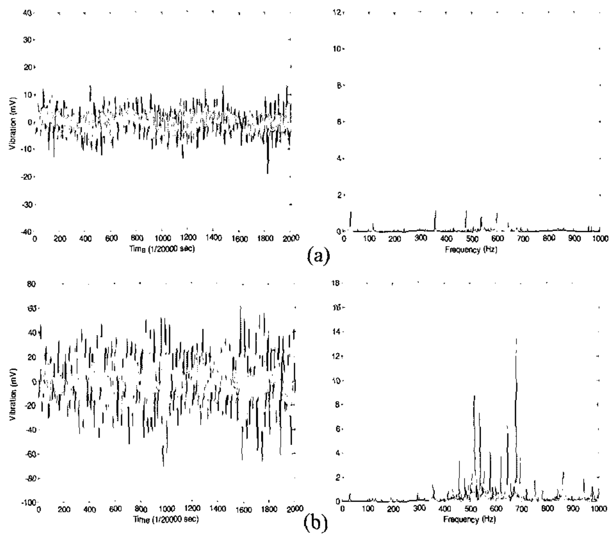


Fig. 3. Bearing time-domain vibration signals and FFT spectrum, (a) normal, and (b) defective bearing

By collecting the vibration data of defective and normal bearings to create a training database, the paper investigates a way to optimize the fuzzy system based on that data. Combining fuzzy logic and neural network in the ANFIS archives a neuro-fuzzy system that can optimize the system model from the given input-output data. The genetic algorithm (GA) is also used to optimize the construction of the ANFIS system.

Each set of vibration data has 10000 samples at 20000Hz sampling rate. The time-domain feature considered is maximum value of the amplitude of vibration signal:

$$x_{\max} = \max_{n=0}^{N-1}(d(n)) \tag{1}$$

FFT transform is performed to extract the frequency features of vibration signal, and each basic bearing frequency is considered in the 5 Hz frequency band:

$$x_{FFT} = \sum_{F=f-2.5}^{f+2.5} FFT\left(\left|\frac{F}{\Delta f}\right|\right), \Delta f = \frac{1}{T_s} \tag{2}$$

where, T_s is sampling time.

Spectrum feature referred to as input of ANFIS is the sum of all bearing basic frequencies. As a result, the bearing condition can be detected whether it is good or not, but it is impossible to find out what type of bearing fault it is.

The bearing used in this paper has basic frequencies: BPOF (ball pass outer race frequency) = 3.57 x rps (revolutions in second), BPIF (ball pass inner race frequency) = 5.429 x rps, BSF (ball spin frequency) = 4.632 x rps, and FCF (fundamental cage frequency) = 0.396 x rps.

Fig. 4 shows 2 sets of features extracted from vibration data in both defect and normal conditions.

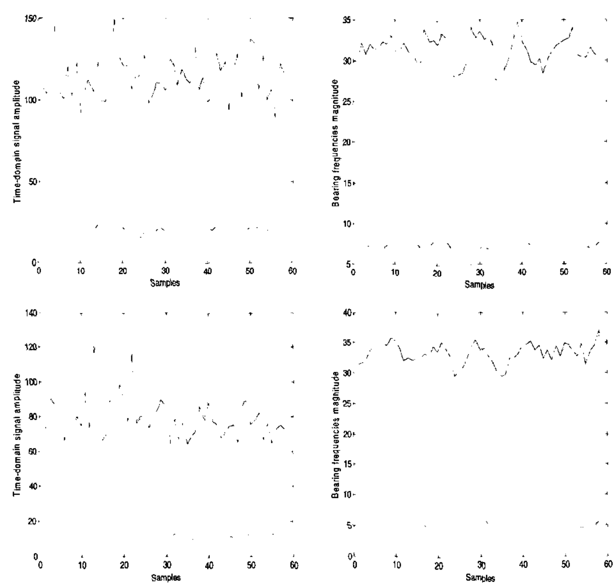


Fig. 4. Some bearing training patterns, defective (-) and normal (--)

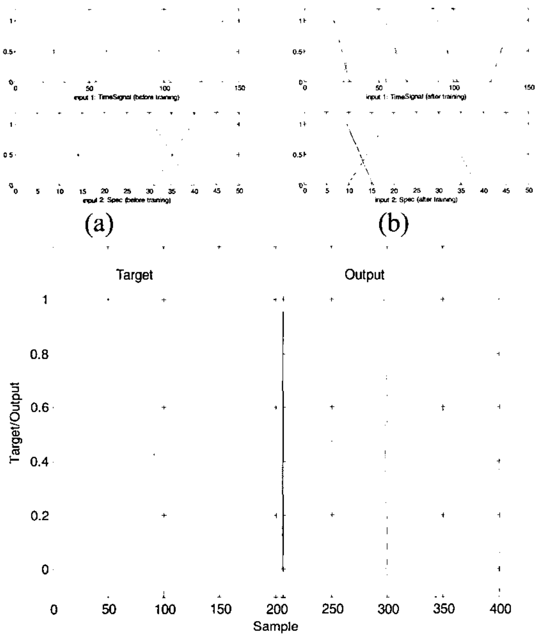
4. Training and Experiment Results

The GA algorithm has a 50-chromosome population size, and uses 50 generations to search for optimal ANFIS configuration. The training and simulation were performed by Matlab software. The training data set has about 1200 samples extracted from measured bearing vibration data. Table 1 shows the local optimum results obtained from the genetic program, which chooses the local optimal number of input membership functions, a type of input-output membership function (MF) corresponding to each averaging training error.

Table 1. Local optimum parameters are obtained from GA algorithm

(1)	(2)	(3)	(4)	(5)	(6)	(7)
10	0.0168	5	5	gbellmf	gaussmf	linear
40	0.0140	5	5	gbellmf	trimf	linear
60	0.0129	5	5	gbellmf	gbellmf	linear
80	0.0097	5	5	gbellmf	gaussmf	linear
100	0.0086	5	3	gbellmf	gbellmf	linear
110	0.0068	5	3	gbellmf	gbellmf	linear
120	0.0040	5	5	gbellmf	gbellmf	linear
130	0.0022	5	5	gbellmf	trimf	linear
150	0.0000	5	3	trapmf	trapmf	constant

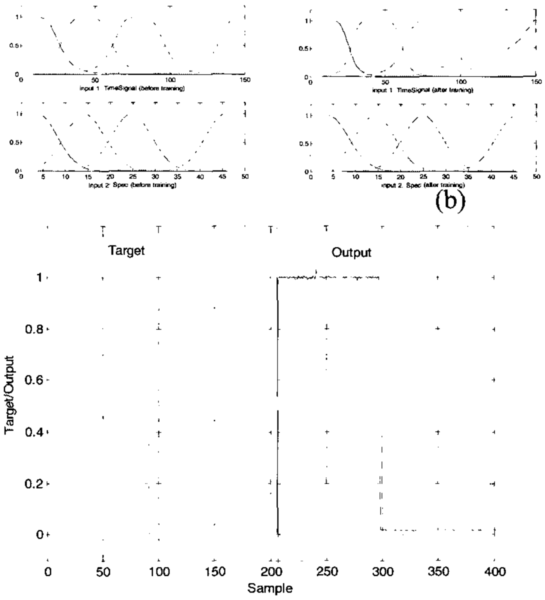
(1) - Training epochs
(2) - Average training error
(3) - Number of MFs (input 1)
(4) - Number of MFs (input 2)
(5) - MF type (input 1)
(6) - MF type (input 2)
(7) - MF type (output)



(c)

Fig. 5. Input membership functions (training with 150 epochs) (a) before training, (b) after training, and (c) targets and ANFIS system output

The model in Fig. 5 is trained with the prepared data and terminated at the 150th epochs with 100% training accuracy. The initial membership functions {trapmf (5), trapmf (3)} are shown in Fig. 5(a), and Fig. 5(b) presents post-training. Output membership function is constant type, and the comparison between target output and predicted output is also indicated in Fig. 5(c).



(c)

Fig. 6. Input membership functions (training with 80 epochs), (a) before training, (b) after training, and (c) targets and ANFIS system output.

The same explanation can be applied to Fig. 6, but, in this case, the model used input membership function set {gbellmf (5), gaussmf (5)} is trained till 80 epochs, and training error is 0.0097. The output membership function used in this case is linear type.

From Table 1, the best training accuracy obtained with the given training data when input membership is *{trapmf (5), trapmf (3)}* and output membership is *{constant}* after 150 epochs training. Other structures are also acquired with smaller number of epochs but larger averaging training error, which is perhaps appropriate for systems that need to update the training database frequently to reduce time. Tests are performed in two of the above mentioned models and the accurate predictions are achieved, which are almost the same as the targets in case of Fig. 5. Once the optimal parameters have been found, such a fuzzy system can be supposed as an optimal model for bearing diagnosis. This selection is done offline and can be used for online diagnosis once the parameters are available. The new parameters are also reselected easily using GA if the data is updated or modified. Therefore, it can be concluded that using GA for selecting the optimal configuration of ANFIS is a powerful technique; where the GA program can search for the optimal structure of the fuzzy modeling based on the given training data.

5. Conclusion

This paper investigated a way to optimize the fuzzy modeling on ANFIS architecture applied to bearing diagnosis.

Parameters and structure of the model are obtained on the base of neural network and genetic algorithm. Averaging error of ANFIS is selected as fitness function of the genetic program, and the model can get a local optimal design with each of the selected training epochs.

The structure results may not suitable for another machine. Training data have to be collected with different types and levels of bearing conditions to achieve better predictions because the model can obtain the suitable structure based on those extracted data features. A rich and reliable database can improve the reliability of the proposed model.

Acknowledgements

The authors would like to thank the University of Ulsan, the Ministry of Commerce, Industry and Energy (MOCIE) and Ulsan Metropolitan City that partly supported this research through the Network-based Automation Research Center (NARC).

References

[1] B. Samanta, K. R. Al-Balushi, S. A. Al-Araimi, "Artificial neural networks and genetic algorithm for bearing fault detection", *Soft Comput*, vol. 10, 264-271, 2006.

[2] Xinsheng Lou, Kenneth A. Loparo, "Bearing fault diagnosis based on wavelet transform and fuzzy inference", *Mechanical Systems and Signal Processing*, vol. 18, 1077-1095, 2004.

[3] B. Samanta, K. R. Al-Balushi, "Artificial neural network based fault diagnostics of rolling element bearings using time-domain features", *Mechanical Systems and Signal Processing*, vol. 17, 317-328, 2003.

[4] Changzheng Chen, Changtao Mo, "A method for intelligent fault diagnosis of rotating machinery", *Digital Signal Processing*, vol. 14, 203-217, 2004.

[5] Z. Ye, A. Sadeghian, B. Wu, "Mechanical fault diagnostics for induction motor with variable speed drives using Adaptive Neuro-fuzzy Inference System", *Electric Power Systems Research* , vol. 76, 742-752, 2006.

[6] Gregory Goddu, Bo Li, Mo-Yuen Chow, James C. Hung, "Motor Bearing Fault Diagnosis by a Fundamental Frequency Amplitude Based Fuzzy Decision System", *in IECON'98 Proceedings of the 24th Annual Conference of the IEEE*, Volume 4, 1961-1965, 1998.

[7] Jyh-Shing, Roger Jang, "ANFIS: Adaptive-Network-Based Fuzzy Inference System", *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 23 No. 3, 1993.

[8] Branimir B. Jovanovic, Irini S. Reljin, Branimir D. Reljin, "Modified ANFIS Architecture – Improving Efficiency of ANFIS Technique", *7th Seminar on Neural Network Applications in Electrical Engineering*, NEUREL-2004.

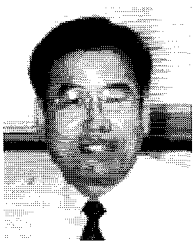
[9] Cornelius T. Leondes, *Fuzzy Theory Systems: Techniques and Applications*, Academic Press, 1999, Volume 1, 205-221.

[10] J. S. Rao, *Vibratory Condition Monitoring of Machines*, Alpha Science International Ltd., 2000.

[11] Keith A. Woodbury, "Application of Genetic Algorithms and Neural Networks to the Solution of Inverse Heat Conduction Problems", *A Tutorial.*

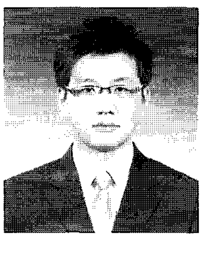
[12] Bo Li, Yodyium Tipsuwan, James C. Hung, "Neural-Network-Based Motor Rolling Bearing Fault Diagnosis", *IEEE Transactions on Industrial Electronics*, Vol. 47, No. 5, 2000.

[13] Abhinav Saxena, Ashraf Saad, "Evolving an artificial neural network classifier for condition monitoring of rotating mechanical systems", *Applied Soft Computing*, 2006.



Hong-Hee Lee
He received his B.S., M.S., and Ph.D. degrees from Seoul National University, Seoul, Korea. He is a Professor in the School of Electrical Engineering, University of Ulsan, Ulsan, Korea. He is also Director of the Network-based Automation Research Center (NARC), which is sponsored by the Ministry of Commerce, Industry and Energy (MOCIE). His research interests are power electronics, network-based motor control, and control networks. He is a member of IEEE, KIEE, KIPE and ICASE.

Ngoc-Tu Nguyen
He received his B.S. and M.S. degrees from the Faculty of Electronics and Electrical Engineering, Ho Chi Minh City Uni. of Technology, Vietnam. He is currently a Ph.D. student at the School of E.E., University of Ulsan, Korea. His research interests are electrical machines, fault diagnostics, and power electronics.



Jeong-Min Kwon
He received his B.S. and M.S. degrees from the School of E.E., University of Ulsan, Korea. Currently, he is a Ph.D. student at the University of Ulsan. His research interests are electrical machines, fault diagnostics, and power electronics.