Gearbox fault detection using static data and adaptive neuro-fuzzy inference system

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Abstract

Condition monitoring of a gearbox is a crucial activity due to its importance in power transmission for many industrial applications. Thus, there has always been a constant pressure to improve measuring techniques and analytical tools for early detection of faults in gearboxes. This study forces to develop the gearbox monitoring methods using the operating parameters obtained from machine control processes rather than the traditional measurements such as vibration and acoustics. To monitor the gearbox conditions, an adaptive neuro-fuzzy inference system (ANFIS) is used to captures the nonlinear connections between the electrical motor current and control parameters such as load settings and temperatures. The predicted values generated by ANFIS model are then compared with the measured values to indicate the abnormal condition in gearbox. The experimental results show that ANFIS model is adequate and is able to serve as an efficient tool for gearbox condition monitoring and fault detection.

1. *Introduction*

Condition monitoring (CM) is a technique for acquiring different datasets and analyzing them to assess the health and condition of equipment. Thus, potential problems can be detected and diagnosed at an early stage in their development, providing the opportunity to take suitable recovery measures before they become so severe as to cause machine breakdown. To obtain accurate results, CM collects large amount of data with wide diversity including operating parameters, high density dynamic signals and special event datasets to produce historical trends which are presented to engineers and stored in databases. This gives rise to the problem that the volume of data is very large and the relationship between measurements is very complicated. Consequently, the CM data is not always understood properly (McArthur et al., 2004) and the extraction of useful and meaningful information from the data is extremely challenging. In addition, because machine and sensor technologies are growing in complexity in association with the recent progress in information technology, data acquisition systems can produce an overwhelming amount of data which is continuously increasing and contains features representing hundreds of attributes.

Vibration is a widely used signal in the condition monitoring and fault diagnosis systems of rotating machinery (Bouillaut et al., 2001; Wilson et al., 2001; Monsen et al., 1993). To process vibration signal, several signal processing tools have been proposed. These include time domain averaging, power spectrum, cepestrum, demodulation, adaptive noise cancellation, time-series analysis, high-order statistics, time-frequency distribution, wavelet, etc., (Baydar et al., 2001; Lin et al., 2003; Yang et al., 2002) and show good results in detecting gearbox faults. However, these techniques often need an additional vibration measurement system, which leads to high cost of the monitoring system. Alternatively, static data being another signal can be used for detecting and diagnosing the faults in gearboxes. It is contains mainly measurements from the controller, which are used to demonstrate the performance characteristics of the system. Additionally, this type of data can give a quick indication of system health. The static data, which are available in most of machines, including armature current, load set, speed feedback, torque feedback, motor current, speed demand and have been explored based on a gearbox test system.

Among the different methods for condition monitoring of rotating machinery, artificial neural networks (ANN), which have become an outstanding method exploiting their non-linear pattern classification properties in the recent decades, have been offering advantages for automatic detection and identification of gearbox failure conditions, whereas they do not require an in-depth knowledge of the behaviour of the system. However, ANNs are not interpretable and understandable, i.e. they are incapable of explaining a particular decision to the user in a human-comprehensible form. Conversely, fuzzy logic has the ability of modeling human knowledge in a form of if-then rules using easily understandable linguistic term. It has the capability of transforming linguistic and heuristic terms into numerical values for use in complex machine computation via fuzzy rules and membership functions. The if-then rules as well as the initial parameters of membership functions are normally prepared by an expert. Thus, fuzzy logic requires fine-turning in order to obtain acceptable rule base and optimize parameters for available data. For these reasons, fuzzy logic is combined with ANN to utilize the learning abilities of neural networks with human knowledge representation abilities of fuzzy systems. Adaptive neuro-fuzzy inference system (ANFIS) is one of the kind combinations, which is an integration of a fuzzy inference system with a back-propagation algorithm (Jang et al., 1997; Lin et al., 1996). In recent years, many investigations have been performed to apply the ANFIS system for modelling of the engineering processes (Li et al., 1996; sun et al., 2005; Hasilogu et al., 2004). This paper examines the performance of a model based condition monitoring approach by using just operating parameters for fault detection in a two stage gearbox. It has the potential to achieve cost effective monitoring system because the operating parameters are available in many systems. A model for current prediction is developed using an ANFIS to captures the nonlinear connections between the electrical motor current and control parameters such as load settings and temperatures. The predicted values generated by ANFIS model are then compared with the measured values to indicate the abnormal condition in gearbox.

2. Architecture of ANFIS

ANFIS architecture consists of five layers in which the first and the fourth layers are adaptive nodes while the remaining layers are fixed nodes. The adaptive nodes are associated with their respective parameters, get duly updated with each subsequent iterations while the fixed nodes are devoid of any parameters (Hamidian et al., 2010; Sengur, 2008; Das et al., 2010).This system contains two inputs namely x and y and one output f which is associated with the following rules:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p_1x + q_1y + r_1$)

Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p_2x + q_2y + r_2$)

where x and y are the inputs, A_i, B_i and f_i are fuzzy sets and systems output respectively. p_i, q_i and r_i are the design parameters that are determined during the training process.

The ANFIS architecture to implement these two rules is shown in Figure 1, in which a circle indicates a fixed node, whereas a square indicates an adaptive

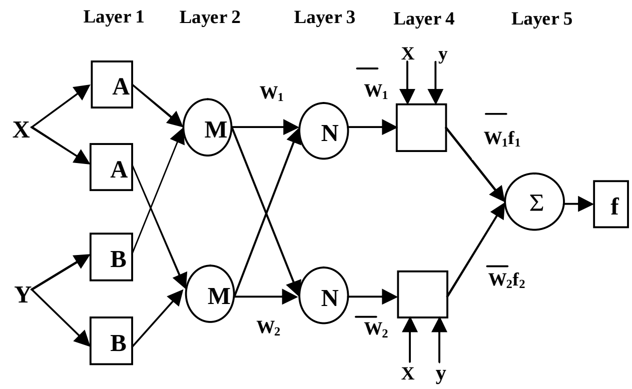


Figure 1 Architecture of ANFIS

Layer 1 - fuzzification layer: Every node I in this layer is an adaptive node. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by

$$O_i^1 = \mu_{A_i}(x), i = 1,2 \tag{1}$$

$$O_i^1 = \mu_{B_{i-2}}(y), i = 3,4 \tag{2}$$

where x and y are the inputs to node i, A is a linguistic label (small, large) and $\mu_{A_i}(x)$, $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function. Usually we choose $\mu_{A_i}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{3}$$

Here (a_i, b_i and c_i) are the parameters of the membership function. Parameters are referred to as premise parameters.

Layer 2 - rule layer: a fixed node labelled M whose output is the product of all the incoming signals, the outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), i = 1,2 \tag{4}$$

Layer 3 - normalization layer: this layer are also fixed node and is labelled *N*

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \tag{5}$$

Layer 4 - defuzzification layer: an adaptive node with a node the output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{6}$$

where $\overline{w}_i$ is the output of the layer 3. p_i, q_i and r_i are parameter set.
Layer 5 - summation neuron: a fixed node which computes the overall output as the summation of all incoming signals

$$O_i^5 = \sum \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

3. Learning algorithm of ANFIS

As mentioned earlier, both the premise (non-linear) and consequent (linear) parameters of the ANFIS should be tuned, utilizing the so-called learning process, to optimally represent the factual mathematical relationship between the input space and output space. Normally, as a first step, an approximate fuzzy model is initiated by the system and then improved through an iterative adaptive learning process. Basically, ANFIS takes the initial fuzzy model and tunes it by means of a hybrid technique combining gradient descent back propagation and mean least-squares optimization algorithms. At each epoch, an error measure, usually defined as the sum of the squared difference between actual and desired output, is reduced. Training stops when either the predefined epoch number or error rate is obtained. There are two passes in the hybrid learning procedure for ANFIS. In the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent (Jang, 1993).

4. Gear fault simulation

A tooth breakage is one of common faults in gearbox. Different levels of breakages on the pinion gear are examined in this part of research. Three levels of fault severity: 25%, 50% and 75% of a tooth are removed from three pinion gears respectively. Figure 2 illustrates the details of the faults for Gear 07 with 25% tooth breakage and Gear 08 with 50% tooth breakage. Although the defects look very large they not influence the transmission significantly because of high overlap ratio of the gear set

a) Gear No 7 with 25% tooth breakage (Baseline)

b) Gear No 8 with 50% tooth breakage

Figure 2 Gear faults

5. ANFIS model development

5.1 Data characteristics

The data were collected for the three gear sets: Gear07, Gear08 and Gear09 using a same gearbox case. Gear07, Gear08 and Gear09 were induced with 25%, 50% and 75% tooth breakage respectively. As there was not a healthy gear for more tests, Gear07 with the smallest gear fault are taken as the baseline for model development. To evaluate the neural network, only three variables: AC current, load set points and gearbox temperate are explored for full understanding of the principle behind. Figure 3 respectively shows eight data sets collected from eight independent tests based on Gear 07. It can be seen that each data set shows a gradual increase in the current with increase in load and temperature of the gearbox. The rate of current increase with load settings is very high and in a nonlinear behavior, which indicate a complicated correlation between the current and load setting and it is not easy to model it with a simple method. In addition, the temperature also shows considerable influences on the current. As can be seen in Figure 3, a slight inverse influence on the current can be observed. However, the decrease rate becomes smaller at higher temperature, which again indicates a more complicated model is required to describe the connections between electrical current, load settings and temperature influences

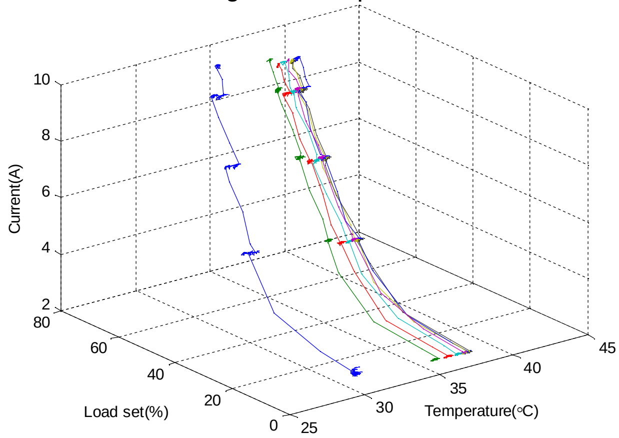


Figure 3 Data characteristics of current with temperature and load of gear in Gear 07

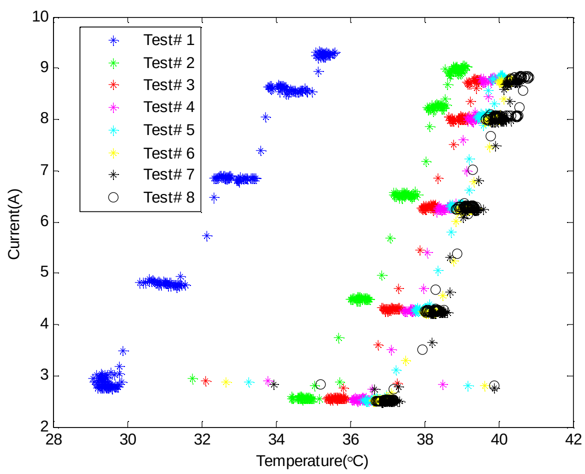


Figure 4 Data characteristics of current with temperature of gear in Gear 07

Figure 4 shows more details of the temperature influence. It can be seen that the current decreases with the increase in temperature at each load setting. It may be due to that the damping effect of lubrication decreases with temperature. Nevertheless, the correlation also shows a nonlinear way. As this temperature influence is very clear, it will certainly impact the model development. Fault detection must include this influence for obtaining more accurate results

5.2 Model development

The ANFIS model is developed using the baseline datasets from Gear 07. The model has two inputs: temperature and load set points and AC current. For each input, a bell shape is chosen for each membership function (MF) and the number of MFs is 2. To train the ANFIS model, the datasets from Gera07 involved 2088 data samples from 8 tests of different runs is used. The 2088 data points are divided into two equal subsets of 1044 points: one for ANFIS model training and the other for model verification. In order to evaluate the learning process, the convergence of root mean squared error (RMSE) is utilized. If the decreasing rate of the RMSE as well as the performance is not significant, the learning process can be terminated. Through the learning process, the parameters of MFs are automatically adjusted in order that the outputs of ANFIS model match the actual values in training data. In this study, after executing 300 epochs, all RMSEs of the outputs reach the convergent stage as shown in Figure 5. The initial shapes of MFs and their changes after learning are show in Figure 6. It can be seen that the MF parameters are significantly changed to match the outputs of model with the measured values in the training set. The result of the training process is presented in Figure 7. Obviously, the outputs of ANFIS model are very identical with the measured values, which indicate that ANFIS model has been well trained

5.3 Model evaluation and detection threshold

To confirm the model performance, the 2nd dataset is employed as the input and output of the model developed from the 1st set. To measure the quality of the model in fitting to the second data and to detect abnormalities from new datasets, the root mean square error (RMSE) is denoted as:

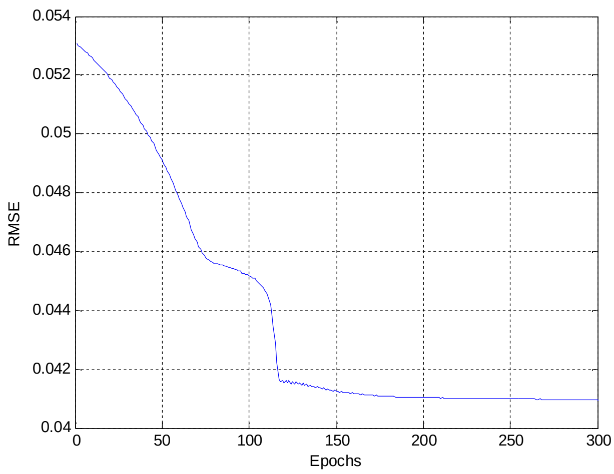
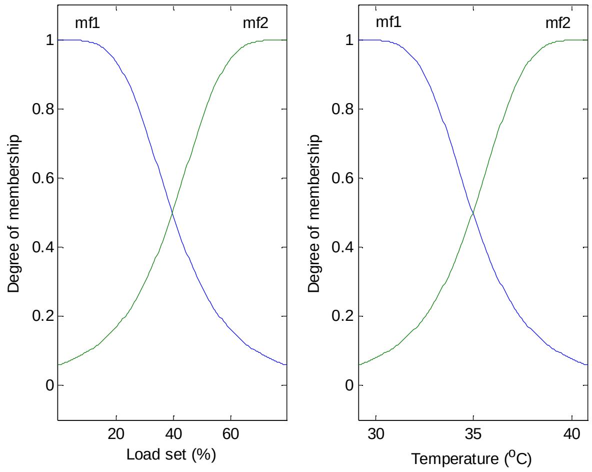
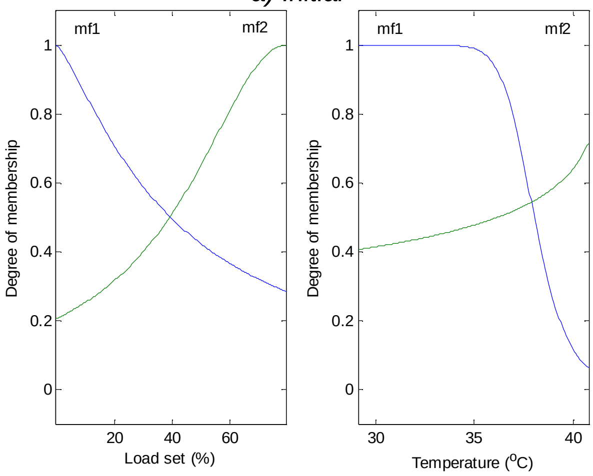


Figure 5 The network RMSE convergence curve



a) Initial



b) Final

Figure 6 Bell shaped MFs

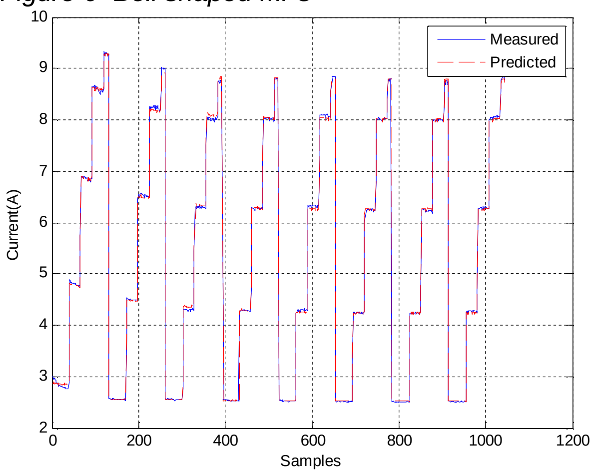


Figure 7 The training result

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_{mi} - I_{pi})^2} \qquad (8)$$

where N is the number of samples, I_{mi} is the actual value determined from measurements, I_{pi} is the predicted values of the ANFIS.

Additionally, a threshold D_{th} defined as 3 times of the root mean squared value between the real measurement and the model prediction is used as a criterion for accepting the testing results and is given (Baqqar et al., 2012):

$$D_{th} = 3\sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_{mi} - I_{pi})^2} \qquad (9)$$

Figure 8 shows model verification results which are calculated using the model using the 2nd part of data from Gear 07. In Figure 8(b), the two dashed lines are the upper and lower detection thresholds respectively. It can be seen that most of the errors obtained by a subtraction between predicted and measured values, are within the threshold, which indicates that the model fits the data with high accuracy. On the other hand it also indicates that the data reflecting the process is healthy.

However, there are some data points exceeding the threshold. These data points are regarded as the outliers arisen from the load transient periods when the temperature measurements have delayed responses to current increases. In general, the model is sufficiently accurate for implementing fault detection for new data sets from other 2 gear sets.

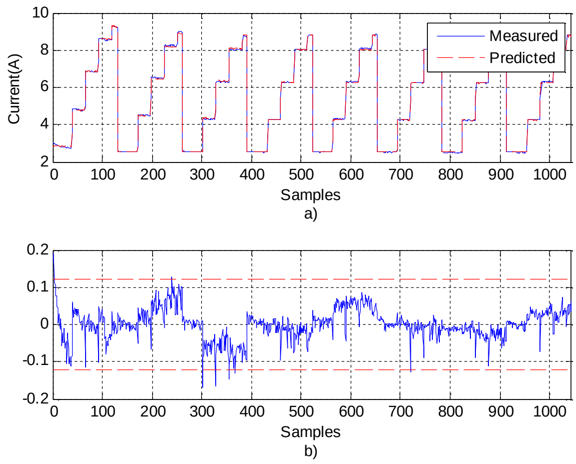


Figure 8 The testing result of ANFIS models a) Measured and predicted results, b) Residual

6. *Fault detection and discussion*

6.1 Fault detection on Gear 08

Figure 9(a) illustrates the measured and predicted current for the gear No. 08 with 50% tooth breakage. It can be seen that the predicted current is very close to the measured one. However, many measurements have observed to have large difference from the predicted one. To perform detection, the residual data which is the difference between the predicted and measured results presented in Figure 9(b) and the details of the data points exceeding the threshold can be seen more clearly. Compared with Figure 8, many successive data points exceed the thresholds and indicate there is a fault in the gear No. 08

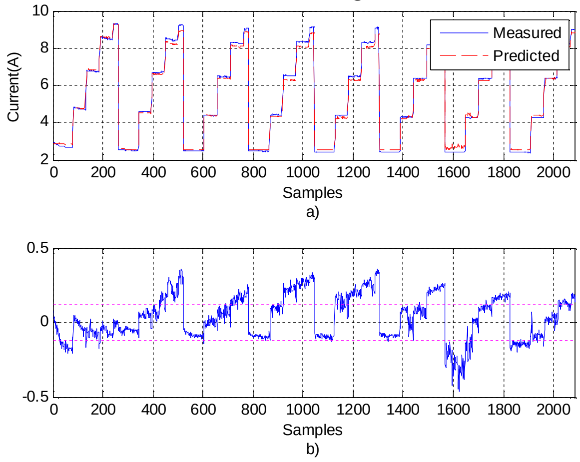


Figure 9 a) Measured and predicted current of the gear No. 08 – 50% tooth breakage, b) The residual

6.2 Fault detection on Gear 09

Similarly, the ANFIS model is used for fault detection of the gear No. 09 which is 75% tooth breakage. Figure 10(a) shows the measured and predicted current of the gear No. 09. It can be seen clearly that the predicted currents have large difference from the measured one. According to the residual presented in Figure 10(b), there are several points exceeded the threshold. In comparison with the residual of the gear No. 08, the overall amplitudes of the errors are much higher and show that this gear has a much severer fault than the gear No. 08

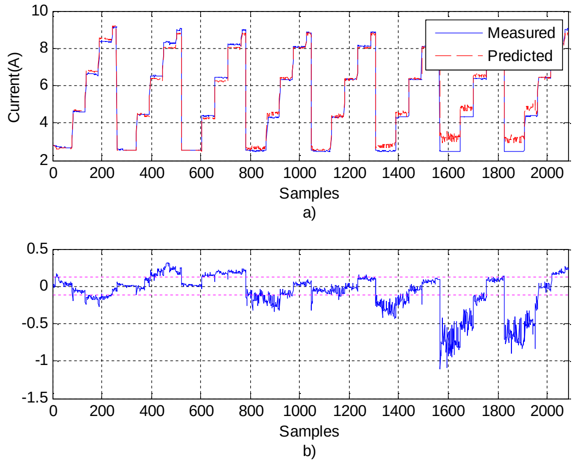


Figure 10 a) Measured and predicted current of the gear No. 09 - 75% tooth breakage, b) The residual

7. Conclusion

This paper confirms that it is possible to use static data which contains mainly measurements from the controller for monitoring mechanical faults in gearbox transmission systems. Based on data characteristics and future integration requirements, the ANFIS approach of gearbox fault detection and diagnosis has been presented for using the static dataset of motor operation. The model developed using a baseline data captures the nonlinear connections between AC current, load setting and gearbox temperature. Test results show that the ANFIS model based method is accurate estimators of the complex gearbox process and allows the generation of differences from baseline and between different gear faults. Therefore, it demonstrates the effectiveness of the proposed method for detecting and diagnosing tooth faults in a two stage gearbox just using motor operating parameters.

References

Baqqar, M., Wang, T., Ahmed, M., Gu, F., Lu, J., Ball, A., (2012). A general regression neural network model for gearbox fault detection using motor operating parameters, *International Conference on Control*.

Baydar, N., Ball, A., (2001). A comparative study of acoustic and vibration signals in detection of gear failures using Winger-Ville distribution, *Mechanical Systems and Signal Processing*, Vol. 15, no. 6, pp. 1091-1107.

Bouillaut, L. and Sidahmed, M., (2001). Helicopter gearbox vibrations: cyclo-stationary analysis or bilinear approach, *ISSPA*, Kuala Lumpur, Malaysia, 13-16 August.

Das, A., Maiti, J. and Banerjee, R.N., (2010). Process control strategies for a steel making furnace using ANN with bayesian regularization and ANFIS, *Expert Systems with Applications*, Vol. 37, no. 2, pp. 1075-1085.

Hamidian, D. and Seyedpoor, M., (2010). Shape optimal design of arch dams using an adaptive neuro-fuzzy inference system and improved particle swarm optimization, *Journal of Applied Mathematical Modelling*, Vol. 34, no. 6, pp.1574-1585.

Hasiloglu, A., Yilmaz, M., Comakli, O., Ekmekci, I., (2004). Adaptive neuro-fuzzy modeling of transient heat transfer in circular duct air flow, *International Journal of Thermal Sciences*, Vol. 43, pp. 1075-1090.

Jang, S., (1993). ANFIS: Adaptive network-based fuzzy inference system, IEEE on Systems, Man and Cybernetics, Vol. 23, no. 3, pp. 665-685.

Jang, S., Sun, T. and Mizutani, E., (1997). *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine intelligence*, Prentice Hall, Inc.

Li, C.H., Zhu, X.J., Cao, G.Y., Hu, W.Q., Sui, S., Hu, M.R., (2009). A maximum power point tracker for photovoltaic energy systems based on fuzzy neural networks, *Journal of Zhejiang University SCIENCE*, Vol. 10, no. 2, pp. 263-270.

Lin, J., Zuo, M.J., (2003). Gearbox fault diagnosis using adaptive wavelet filter, *Mechanical Systems and Signal Processing*, Vol. 17, no. 6, pp. 1259-1269.

Lin., C. and Lee, C., (1996). *Neural Fuzzy Systems-A Neuro Fuzzy Synergism to Intelligent Systems*. Prentice Hall.

McArthur, S., Strachan, S. and Jahn, G., (2004). The design of a multi-agent system for transformer condition monitoring, *IEEE Transactions on Power System*, Vol. 19, no. 4, pp. 1845-1852.

Monsen, P.T., Manolakos, E.S., Dzwonczyk, M., (1993). Helicopter gearbox fault detection and diagnosis using analogy neural network , *Signals, Systems and Computers, 27th Asilomar Conference*, 1-3 November, Vol. 1, pp. 381–385.

Sengur, A., (2008). An expert system based on linear discriminant analysis and adaptive neurofuzzy inference system to diagnosis heart valve diseases, *Expert Systems with Applications*, Vol. 35, no. 1-2, pp. 214-222.

Sun, T., Yan, S.J., Cao, G.Y., Zhu, X.J., (2005). Modelling and control PEMFC using fuzzy neural networks, *Journal of Zhejiang University SCIENCE*, Vol. 6, no. 10, pp. 1084-1089.

Wilson, Q.W., Ismail, F. and Golnaraghi, M.F., (2001). Assessment of gear damage monitoring techniques using vibration measurements, *Mechanical Systems and Signal Processing*, Vol. 15, no. 5, pp. 905-922.

Yang, D.M., Stronach, A.F., MacConnell, P., Penman, J., (2002). Third-order spectral techniques for the diagnosis of motor bearing condition using artificial neural networks, *Mechanical Systems and Signal Processing*, Vol.16, no. 2-3, pp. 391-411.