Machine Condition Monitoring through Frequency Analysis of Maintenance Records: A Neuro-Fuzzy Approach

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Abstract: *Machine condition monitoring and fault diagnosis fields are charged with developing new technologies to detect and diagnose the machinery problems. In fact, several methods of fault diagnostics have been developed and applied effectively to identify the machine faults at an early stage using different quantities (Measures or Readings) such as current, voltage, speed, temperature, and vibrations. The major problem of diagnosis techniques is that they require constant human interpretation of the results; therefore, the research has been underway for a longtime to automate the diagnosis process. Recently, artificial intelligence-based techniques (e.g., neural networks, fuzzy logic, genetic algorithms, hybrid methods, and intelligent agents) have been recently utilized widely with the monitoring system to support the diagnosis system. In this paper, a machine condition monitoring and diagnostic system is introduced with experimental verification. An adaptive neuro-fuzzy inference system (ANFIS) is used to monitor and predict the fault types. The system uses a piezoelectric accelerometer to generate a signal related to machine condition and fault type. The power spectral density (PSD) of this signal is used as an input to ANFIS, which in turn outputs a value for predicted fault type. Experimental validation runs were conducted to compare the actual fault types with the predicted ones. The comparison shows that the adoption of trapezoidal membership function in ANFIS achieved a very satisfactory fault prediction accuracy of 99.9%.*

Keywords: *Condition Monitoring, Frequency Analysis, Neuro-Fuzzy*

1 Introduction

Maintenance costs are normally a considerable portion of the product cost. According to the investigation of a wide spectrum of industry, the costs of maintenance account for 15% - 40% of the whole production, and one third of which is caused by unnecessary and inaccurate maintenance Yu [32]; Lofsten, [2]. Therefore, advanced maintenance methods should be implemented. In recent years, In intelligent maintenance management system, IMMS, the three “isolated islands” of the automation system (i.e., monitoring and forecasting, diagnosis and prognosis, and maintenance decision making) are integrated into an organic system, and maintenance improved by sharing information among these systems. Most real life physical systems are nonlinear, ill-defined and uncertain which makes them difficult to model by conventional mathematical means. Neuro-fuzzy techniques combine elements of both fuzzy logic and neural networks algorithms. This relatively new technique overcomes limitations of the pure fuzzy approach such as the dependency on the expert for fuzzy rule generation and for the design of the non-adaptive fuzzy set. The adaptive neuro-fuzzy inference system (ANFIS) is one such neuro-fuzzy approach. Condition-based maintenance (CBM) is a method used to reduce the uncertainty of maintenance activities, and is carried out according to the need indicated by the equipment condition British Standard Institution [5]. In the last decade, a number of computational tools have been developed for condition-based maintenance and some research results of decision support systems (DSS) for industry-based maintenance have emerged in the literature.

This study was motivated by the problem of improper condition-based maintenance strategy of a process industry (Potash production). Actually, the exploitation of the equipment maintenance records is often a weak point within an operations management organization. Inexistence of proper computerized maintenance system, lack of competences to properly handle maintenance data, or reduced knowledge in advanced maintenance processing techniques, are common problems to solve in order to benefit from the historical record of failures and maintenance operations carried out at certain equipment. In this paper, the maintenance records analysis is used to provide critical information from past experience to improve current maintenance process in the Potash Company. A neuro-fuzzy technique (i.e., ANFIS) of frequency-based analysis is used to build an intelligent condition monitoring system to predict the type of fault or failure for one of the critical production units. This paper is organized as follows: Section 1 is an introduction. Intelligent condition monitoring and fault diagnosis system will be given in the second section. Section 3 is about accelerometer data analysis and presentation. Structure of adaptive neuro-fuzzy inference system will be discussed in section 4. ANFIS for machine condition monitoring is the subject of section 5. Section 6 will demonstrate the validation runs. The last section is to conclude.

2 Problem Formulation

2.1 Intelligent Machine Condition Monitoring System

It is well recognized that optimized maintenance practices within an industrial setting require the correct blend of maintenance strategies. Condition-based (reliability centered, predictive, proactive) maintenance is an important part of this blend for many compelling reasons Mechefske, [3]. Condition monitoring and diagnostics is also becoming recognized more widely as an integral part of automated systems. However, detection and identification of machinery faults can be difficult in monitoring and diagnostics activities.

The aim is to develop an efficient hybrid method for capturing the machine information by means of artificial intelligence, AI, to decode the intelligence supplied from the system. Artificial intelligence techniques such as expert systems, neural networks, genetic algorithms, and fuzzy logic, have been widely applied in mechanical equipment monitoring and diagnosis with different aspects and degrees. It also noticed that different techniques have their unique advantages and disadvantages, and usually cannot replace each other.Many machinery fault diagnostic techniques use automatic signal classification in order to increase accuracy and reduce errors caused by subjective human judgment. Detection of machine faults like mass imbalance, rotor rub, shaft misalignment, gear failure, and bearing defects is possible by comparing the vibration signals of a machine operating with and without faulty conditions. These signals can also be used to detect the incipient failures of the machine components through online monitoring system, reducing the possibility of catastrophic damage. Although often the visual inspection of the frequency-domain features of the vibration signals is adequate to identify the faults, there is a need for a reliable, fast, and automated procedure of diagnostics. Proper monitoring of machinery vibration levels is highly cost-effective in minimizing maintenance down time – both by providing advanced warning and lead time to prepare appropriate corrective actions, and by ensuring that the system does not deteriorate to a condition where emergency action is required. In this paper, the main problem of the Potash industry (i.e., Arab Potash Company, APC) is the visual inspection of frequency analysis performed at the preventive maintenance department. Although they have a very progressive maintenance software system used to assent the conjuncture of their machines, as an attempt to control the break downs and the health conditions of the machines, the visual inspection by maintenance staff results in big discrepancies between the predicted and actual faults, thus causing time delays, inconsistencies, increased inaccurate maintenance activities, and of course increased loss of money.

To solve this problem, an adaptive neuro-fuzzy inference system (ANFIS) was used in this paper to replace the human operator for predicting the faults types from the generated frequency analysis. One of the most important and critical components (namely; the crystallizer agitator) was selected to apply our ANFIS-fault diagnosis system. Recently, this component has faced many unsuccessfully predicted breakdowns and failures, which resulted in unnecessary money loss. The crystallizer agitator is considered a critical component because its breakdown could easily cause production shut down or delay. Special software is used at this Potash industry to generate a frequency analysis of the vibration time signal coming from a piezoelectric transducer mounted on the agitator component. The frequency pattern of the time signal is clear but a visual inspection and prediction usually results in an inaccurate diagnosis of the fault type.

2.2 Accelerometer Data Analysis and Presentation

Machines faults diagnosis and prediction requires generating representative and useful information about the vibration features by means of a sensor. Our approach to predict the fault type is to mount a piezoelectric accelerometer on the machine's component under study in order to give a time-series signal which is supposed to contain useful information about the machine's faults, failures and health conditions. Figure 1 show a photograph of the crystallizer agitator where the piezoelectric transducer is mounted to measure the vibration signal. In the analysis of time series signals, certain restrictions are imposed by the length of the data window (T), being analyzed and by the sampling rate (f_s), used when digitizing continuous data Rogers et al., [4]. This is needed a standard time duration used at the Potash production plant to pick up useful vibration signals for frequency analysis.

Analysis shows that it is difficult to get useful information about the faulty features by only considering the time-series signal. Transformation of data to the frequency domain is done to gain more insight about the vibration features and to help identify the machine's fault or failure. Analyses that transform data into the frequency domain result in displays of acceleration power spectral density (PSD) versus frequency.

Two pieces of information define one segment of time series data: the length of the segment, T, and the sampling time, dT, used in the acquisition data. The sampling time used must be appropriate for the data of interest because it determines the highest frequency component which can be faithfully reconstructed in spectral calculations. This value is called the Nyquist frequency, f_N, where,

$$f_N = \frac{N}{2T} \qquad (1)$$

$$dF = \frac{f_s}{N} \qquad (2)$$

Where dF is the finest frequency resolution. The length of time signal, T, is the actual total time of vibration measurement. The length of this period is 4 sec.

The power spectral density (PSD) is generated automatically by a special computer software. It is computed directly from the Fast Fourier Transform, $F(m)$, of the time series as indicated in equations (3) and (4):
For even N: Rogers et al., [4].

$$PSD(m) = \begin{cases} \dfrac{2|F(m)|^2}{N.U.f_s} & for\ m = 1,2,....(\dfrac{N}{2}) - 1 \\ \dfrac{|F(m)|^2}{N.U.f_s} & for\ m = 0 \text{ and } m = (\dfrac{N}{2}) \end{cases} \qquad (3)$$

For odd N:

$$PSD(m) = \begin{cases} \dfrac{2|F(m)|^2}{N.U.f_s} & for\ m = 1,2,....(\dfrac{N-1}{2}) \\ \dfrac{|F(m)|^2}{N.U.f_s} & for\ m = 0 \end{cases} \qquad (4)$$

Where:

$$U = \frac{1}{N}\sum_{n=0}^{N-1} \omega_n^2$$

In equations (3) and (4), N is the number of data points sampled during the time segment, T, and ω_n is the natural frequency of the machine's components. Figure 1 illustrates a sample of PSD patterns used to get information about the machine's faulty features, and as inputs to ANFIS to predict the type of fault.

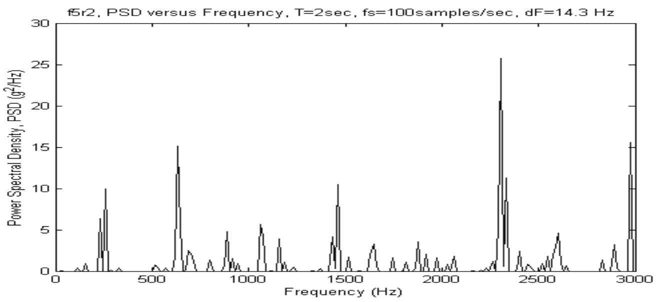

Fig.1 A sample of power spectrum of the vibration time signal picked up from the crystallizer agitator component

2.3 Structure of Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive neuro-fuzzy inference system is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can construct an input-output mapping based on both human-knowledge as fuzzy if-then rules and stipulated input-output data pairs for neural networks training.

Five network layers are used by ANFIS to perform the following fuzzy inference steps: (i) input fuzzification, (ii) fuzzy set database construction, (iii) fuzzy rule base construction, (iv) decision making, and (v) output defuzzification.

ANFIS is more powerful than the simple fuzzy logic algorithm and neural networks since it provides a method for fuzzy modeling to learn information about the data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data, Jang [1]. In the next section, the application of ANFIS to predict the surface roughness on-line is discussed.

2.4 ANFIS for prediction of Machines Fault Types

Constructing intelligent prediction systems requires data representation and transformation of existing problem knowledge to a knowledge engineering schemes and modeling current facts from the domain space to the existing knowledge through inference process.

In this study, we try to investigate the effectiveness of predicting machine's fault types with a relatively new approach method called adaptive neuro-fuzzy inference system (ANFIS). Two vibration-related parameters have been selected, and listed with their meanings and ranges in Table 1. Based on these frequency-based input parameters, and the fault type as an output parameter, ANFIS was built to diagnose the machine's fault type. In this model, we tested different neural network and fuzzy logic parameters to achieve the maximum prediction accuracy of fault types.

Table 1 Input and output parameters used in building ANFIS

Parameter	Meaning	Range
f	Frequency	0 to 30000 *Hz*
A	Amplitude	0.001 to 8.00 *mm/s*
FC	Fault Code	100 to 900

By investigating the power spectra of the time-series signals of all the captured vibration time signals, three main regions may recognize each power spectrum pattern, and carries useful and clear information about the fault inputs and output parameters. Figure 1 shows a sample of the power spectrum for the experimental vibration signals.. The maximum power spectral density (PSD) amplitude (A_i) in each region, and its corresponding frequency (f_i), identify the three regions of the power spectrum, and fed as inputs into the neuro-fuzzy prediction, six power spectrum parameters (*A1*, *f1*, *A2*, *f2*, *A3*, *f3*) are taken, and mapped to the fault type output (*FC*) by using ANFIS.

ANFIS prediction of machine's fault types starts by obtaining the data set (input-output data pairs) and dividing it into training and checking or validating data sets. The training data set is used to find the initial premise parameters for the fuzzy membership functions by equally spacing each membership function. The values of the premise parameters are fixed, so the overall predicted fault type, *FC*, can be expressed as a linear combination of consequent parameters. Then, the output of ANFIS which is the predicted fault type, can be written as:

$$\begin{aligned} FC = {} & (\overline{w_1}A1)P_1^1 + (\overline{w_1}f1)P_2^1 + (\overline{w_1}A2)P_3^1 + (\overline{w_1}f2)P_4^1 + (\overline{w_1})P_0^1 + \\ & (\overline{w_1}A3)P_1^1 + (\overline{w_1}f3)P_2^1 \ldots\ldots\ldots + (\overline{w_{n^2}}A1)P_1^{n^2} + (\overline{w_{n^2}}f1)P_2^{n^2} + (\overline{w_{n^2}}A2)P_3^{n^2} + \\ & (\overline{w_{n^2}}f2)P_4^{n^2} + (\overline{w_{n^2}}A3)P_1^{n^2} + (\overline{w_{n^2}}f3)P_2^{n^2} + (\overline{w_{n^2}})P_0^{n^2} \qquad (5) \end{aligned}$$

In this model of machine's fault type of equation (5), (*f*, *A*) are the frequency analysis parameters, $\overline{w_1}$ to $\overline{w_{n^2}}$ are the normalized firing strengths of fuzzy rules. The full equation has ($7n^2$) terms, where n^2 is the number of inputs implications. The consequent parameters $\{P_1^1, \ldots\ldots, P_o^{n2}\}$ are tuned off-line using linear least square method, and then updated on-line by a gradient decent back-propagation neural networks.

3 Problem Solution

3.1 Experimental Setup and Simulation of the Prediction ANFIS

The experimental setup of Figure 2 shows the Potash industry component under study (i.e., crystallizer agitator); this agitator rotates to perform the main agitation process of the crystallization operation. Basically, the piezoelectric transducer shown in Figure 1 is mounted on pre-selected points of the agitator in order to pick up vibration time signals at different dates and times according to a pre-defined schedule prepared by the preventive maintenance department. These time data are recorded and stored in a data collection device called (Data Pac) as shown in Figure 1.The vibration time signals and data are then downloaded offline to the computer using a special interface for data transfer. These pieces on vibration information carry important information about the conditions of the machine (i.e., crystallizer agitator). Emonitor Odyssey Delux software is used to generate the frequency analysis and power spectral density for the vibration time signals. Figure 2 illustrates the final outcome from the Emonitor.

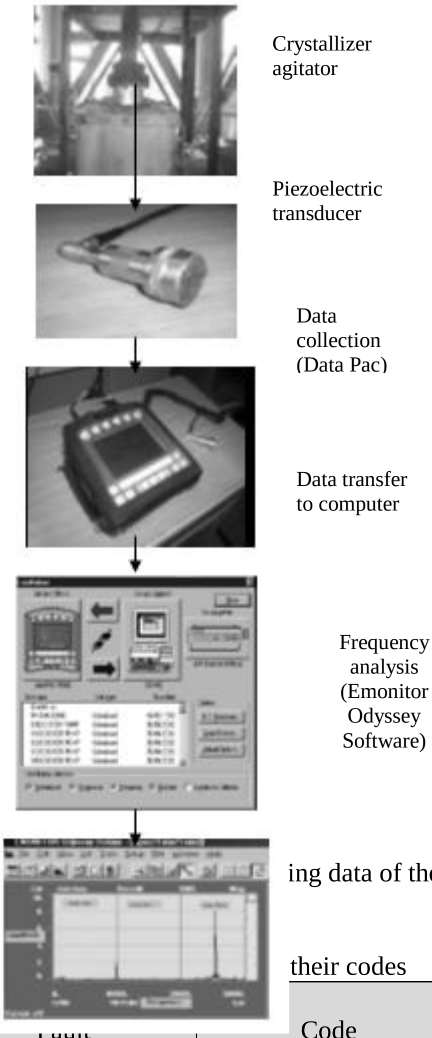

Fig.2 Experimental s … ing data of the prediction ANFIS

… their codes

Fault	Code
No failure	100
Overhung rotor unbalance	200
Eccentric rotor unbalance	300
Angular misalignment	400
Parallel misalignment	500
Mechanical looseness (A)	600
Mechanical looseness (C)	700
Belt problems	800
Bent shaft	900

The piezoelectric transducer used in this study is a three-dimensional accelerometer which generates vibration signals in axial, horizontal, and vertical directions**.** The acceleration time-series signal generated by this accelerometer is captured, filtered by a low-pass filter, buffered, windowed using hanning window, then the power spectral density is computed using the Emonitor software, and the PSD parameters (*A1, f1, A2, f2, A3, f3*) are taken. These power spectrum parameters are fed into the ANFIS as inputs with the fault code, *FC*, as the output. The coding for the faults of the crystallizer agitator used as outputs of ANFIS training is given in Table 2. Actually, 128 data points out of 143 total points in each direction were used to train ANFIS for machine's fault prediction. The remaining 15 independent data points were used for system’s validation.

3.2 ANFIS Training for Prediction of Machine's Faults

ANFIS takes the experimental data of the vibration power spectral density (PSD) parameters (*A1, f1, A2, f2, A3, f3*) as input training data of the system. The fuzzy logic toolbox of MATLAB 7.0 was used to train the ANFIS and obtain the results. Different ANFIS parameters were tested as training parameters in order to achieve the perfect training and the maximum prediction accuracy. Figure 4 shows the fuzzy inference system (FIS) of ANFIS.

A total of 403 network nodes and 192 fuzzy rules were used to build the fuzzy inference system. A trapezoidal membership function (MF) was adopted to train ANFIS because it achieved zero training error at 10 epochs, Figure 3 shows that the system is very well-trained to predict the machine's fault type. A perfect training is clear in this figure. Three trapezoidal membership functions (MF) were used for PSD amplitude inputs (*A1*, *A2*, and *A3*), while another four trapezoidal membership functions were adopted for PSD frequency inputs (*f1*, *f2*, and *f3*). The final ANFIS-tuned (MF) for *A1* and *f1* inputs are illustrated in Figures 4.

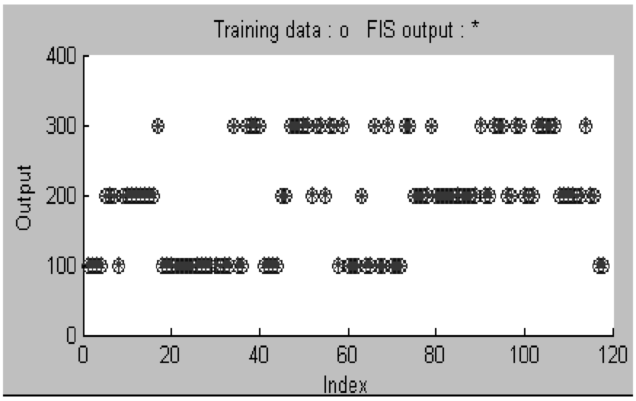

Fig.3 Predicted and actual data

3.3 Validation runs

The machine's fault prediction system was validated by conducting a twelve experimental validating runs. The average percent error in the prediction of machine's faults is almost 0.1%. Table 3 gives a sample of the actual experimental data points, which were used to validate the prediction system. Table 4 gives the actual and predicted fault types along with the absolute percentage error in the prediction.

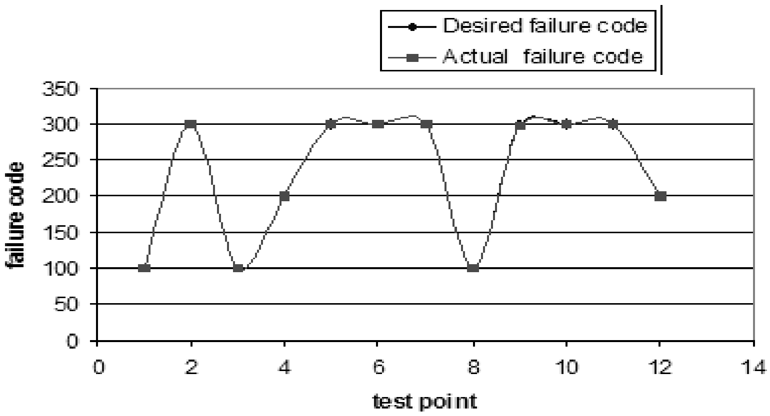

Fig.4 ANFIS validation diagram

Table 3 Input data points for system's validation

Test Point	*A1* *(g^2/Hz)*	*f1* *(Hz)*	*A2* *(g^2/Hz)*	*f2* *(Hz)*	*A3* *(g^2/Hz)*	*f3* *(Hz)*
1	0,203	1614	0,003	15362	0,005	22963
2	0,567	1473	0,304	15421	0,006	25435
3	0,322	1720	0,028	16421	0,003	23354
4	1,598	1473	0,060	13842	0,008	25614
5	0,361	1543	0,301	15894	0,018	25614
6	0,994	1473	0,301	15750	0,008	25614
7	0,446	1052	0,290	15683	0,009	20931
8	0,277	1422	0,046	15929	0,009	22931
9	0,787	1538	0,418	15006	0,004	22816
10	0,701	1473	0,361	15245	0,002	22816
11	0,592	1473	0,361	15245	0,004	22816
12	1,833	1473	0,009	13534	0,003	22522

Table 4 Comparison between actual and predicted faults (validation table)

Test Point	Desired Fault Code	Actual Fault Code	Percent Error
1	100	100,0003	0,00029
2	300	299,9977	0,00077
3	100	100,0003	0,00035
4	200	199,9997	0,0001
5	300	300,0070	0,0023
6	300	300,0025	0,00083
7	300	299,9900	0,0033
8	100	100,0015	0,0015
9	300	298,2500	0,5868
10	300	300,1200	0,0399
11	300	300,2800	0,0932
12	200	199,9997	0,00014
Average % Error			0.0608%

4 Conclusions

An adaptive neuro-fuzzy system is applied to predict and diagnose the machine's faults and failures. The power spectral density parameters (*A1, A2, f1, f2, A3, f3*) were used as inputs to ANFIS to predict the machine's faults. The following conclusions can be drawn from this study:

(1) The average percent error of the machine's faults predicted by ANFIS with the trapezoidal membership function is only 0.1%, achieving an accuracy of 99.9%.

(2) ANFIS analysis shows that the Amplitude, *A*, parameter is more important in condition monitoring than the frequency, *f*, because the final MF of the amplitude are considerably different from the initial ones, while for the frequency, a very little tuning of initial MF parameters is occurred after ANFIS training. This shows the importance of ANFIS model in optimizing the machines condition monitoring process.

(3) ANFIS technique in parallel with power spectrum analysis can be used efficiently to predict and diagnose the machine's faults and failures. It is believed that this approach can be applied to identify other maintenance-related parameters.

The success of this off-line application of an ANFIS system to machines' faults identification suggests that it could also be used for an on-line application, assuming the system is fast enough. The implementation issues and changes necessary to the off-line ANFIS structure and input variables for an on-line application will be the subject of our next step.

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