RELIABLE COMPUTER-BASED MACHINERY FAULT DETECTION

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BIOGRAPHICAL SKETCH

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He has a Ph.D. in Mechanical Engineering from the University of Calgary (Dynamics of Stiffened Plate Structures) and an M.Sc., also in Mechanical Engineering, from the University of Alberta (Fatigue Crack Propagation).

ABSTRACT:

The benefits of condition-based maintenance and current practices in machinery fault detection are reviewed. Problems and costs associated with predictive maintenance are enunciated.

A procedure for the improved detection of faults is examined. Pattern recognition is proposed as a further extension of machinery fault detection techniques. Examples are presented which are encouraging, although it is evident that further research to refine the technique is required.

RELIABLE COMPUTER-BASED MACHINERY FAULT DETECTION

The maintenance of machinery in this day of tight budgets, critical equipment and expensive down-time has become big business. Any procedure or practice which will reduce the overall cost of maintenance, and/or increase the percentage of plant up-time is worthy of consideration.

One such practice is that of on-condition maintenance.

Condition-Based Maintenance

On-condition maintenance is directly related to the old saw "If it ain't broke, don't fix it". That is, all machinery is surveyed regularly in order to determine the current health. If the health indicators are good, nothing is done. Maintenance is carried out only when the machine is known to be developing faults.

The practice of on-condition maintenance involves four aspects:

- detection
- diagnosis
- prognosis
- maintenance activity

The first three of these are under the control of the rotating equipment group, and are commonly grouped under the term "Predictive Maintenance". The fourth is of course performed by the maintenance department.

"Detection" refers to activities which catch the onset of a problem in a machine; usually periodic collection and analysis of vibration data.

"Diagnosis" refers to determining what a detected anomaly is. Now, since you only need to review perhaps 2-3% of your machines, you can collect and analyze more detailed data. At this stage, for example, it would be useful to look at vibration spectra.

"Prognosis" is the third step. Once you have diagnosed the problem, you must decide what to do. Is this a minor repair, do you need a complete overhaul, or is it perhaps time to replace this machine? An experienced person will be needed to make these decisions.

Once these decisions have been taken, the appropriate work orders or purchase orders will be generated and the maintenance department will take over.

The benefits of this approach are numbers:

1) maintenance resources (men and equipment) are expended on incipient problems, rather than on routine overhauls or "fire-fighting"

2) maintenance activities can be logically scheduled, resulting in better allocation of resources (e.g. reduced over-time and reduced under-utilization)

3) problems are not introduced into properly functioning equipment during time-based overhauls, because such equipment is not touched

4) the risk of catastrophic failure is greatly reduced, because the condition of the machinery is monitored from month to month

Cost of Predictive Maintenance

A program which generates such significant benefits has costs:

- personnel are required to record data from many test points

- data must be evaluated; this includes comparison with standards and checking for trends

- equipment must be bought and maintained; this item is especially significant for diagnostic equipment

- personnel must be trained, and these costs can exceed the costs of the equipment, particularly when training a diagnostic specialist

The bulk of the activity in a predictive maintenance program is in the detection phase because the great majority of machines are in good condition at any time; only a few require diagnostic effort. Therefore the detection part of the process should be performed with a minimum expenditure of resources (manpower and other costs).

Detection consists of surveying all the machines and identifying anomalies. Costs will be minimized if we

- use non-specialist personnel
- use highly productive tools
- automate the detection of faults

Predictive maintenance systems which are tailored to non-specialist personnel and to high productivity are commercially available. However, the automated detection of incipient failures is currently in a rudimentary state.

Current Practice

Several methods are presently used in industry. The most common procedure is to compare unfiltered vibration against a fixed alarm level. Alarm levels are typically chosen on the basis of industry standards, but they may be manually varied to suit a particular machine.

Another method, which may be used in addition to the one above, is to flag machines in which the unfiltered vibration has changed by some given percentage. In this case, a machine could be flagged even if its alarm level were not exceeded.

In some cases, alarm levels are related to specific components of the spectrum. These programs typically require more time and more expert personnel, which are more often justifiable for extremely critical machines or for machines which have been flagged by one of the overall readings.

Problems with Current Practice

Since our objective is automated machinery fault detection, these methods have problems:

1) a lot of effort and a fair amount of expertise are required during the system setup

2) they do not take into account idiosyncrasies of machines

3) they do not take into account variations caused by operating conditions

4) users tend to regard the levels as fixed, and therefore inflexible. Used this way, machines may be flagged unnecessarily, and therefore the credibility of the program suffers

5) even where users are inclined to manually adjust the alarm levels according to their personal experience, problems may arise:

    - time is required to analyze the data and determine what adjustments should be made

    - different operators may have conflicting opinions of what the alarms should be

    - time is required to make the changes and thereafter to verify their suitability

An improved method of fault detection is sought; it needs to provide for:

- automatic adaptation to each machine
- little expertise on the part of the user
- little effort on the part of the user, both during startup and after

Proposed Improvements in the Detection of Faults

One approach that seems to overcome these problems is the use of vibration alarms based on simple statistical analyses. As reported by Corley (1), this approach has been taken by ARAMCO.

The procedure involves the calculation of mean and standard deviation of vibration levels for the available history for the entire class of machines. In addition, means and standard deviations are calculated for individual test points rather than for the entire machine class.

The current level is then evaluated:

- ALARM is defined as a level which exceeds the mean plus three standard deviations for the class

- ALERT is defined as a level which exceeds the test point mean plus three standard deviations

In calculating the limit values, exceptionally high readings are neglected in order to avoid creating unacceptably high “norms”. This methodology will be referred to herein as “deviation alarms”.

ARAMCO experience with deviation alarms has proven very satisfactory. It establishes ALARM levels which are more suitable to each machine class. It relates ALERTS to the individual characteristics of each machine and to changing process conditions. It is particularly useful for readings which depend for their meaning on their relative rather than their absolute values.

With suitable computer programming, the limits can be made to update automatically each time more data is stored.

A version of deviation alarms has been added to the DATA-TRAP predictive maintenance system.

Figure 1 shows deviation alarms (ALERTS) detected in some real vibration data, shown in Figure 2. The second last column of Figure 1 shows the calculated limit of mean plus three standard deviations. The last column is the ratio of the latest level, from the column labelled “LAST”, to the limit. Theoretically, as this ratio becomes larger, the detected fault becomes more significant.

Three of the flags raised in Figure 1 relate to bearing defect energy (BDE) measurements taken on rolling element bearings. Conventional alarm levels would be set at about 1.0. Looking at the histories shown in Figure 2, the deviation ALERTs flagged substantial increases before the alarm was reached. This is an important result for this type of measurement for which relative rather than absolute levels are most significant.

The other cases flagged involve casing vibration measured in peak velocity. In one case (131G2A 2H) a peak velocity of only 0.07 ips was flagged. When the normal variations in level are small, as was the case here with a standard deviation of only 0.008 ips, the limit will be tight. This could cause the resulting alarms to be too sensitive; experience will dictate.

When normal variations due to process, load and speed are large, the tolerance is automatically large. This is illustrated by the result for 131G2A 3H BDE.

(1) Corley, James E., Senior Engineering Consultant, Aramco.
“A Vibration Monitoring Program Using Micro-computers”.
Proceedings of the Machinery Vibration Monitoring & Analysis
Meeting of the Vibration Institute, New Orleans, June 26-28, 1984.

******* M777 DEVIATION ALERTS *******

MACHINE	TP	TYPE	LAST	DATE	AVE	RDNGS	S DEV	LIM	SEVERITY
111G2B	1H	IPS	.15	13 3 86	.100	4	.007	.121	1.24
111G2B	1A	IPS	.09	13 3 86	.057	4	.008	.082	1.09
111G2B	3H	IPS	.43	13 3 86	.355	4	.011	.389	1.11
91G3A	1H	BDE	.09	13 5 86	.044	5	.012	.080	1.13
91G3A	2H	BDE	.70	13 5 86	.402	5	.023	.471	1.48
131G2A	2H	BDE	.07	13 5 86	.042	4	.008	.067	1.04
131G2A	3V	BDE	.34	13 5 86	.145	4	.046	.283	1.20
121G12A	1H	IPS	.23	15 5 86	.136	5	.026	.213	1.08
121G12A	2H	IPS	.15	15 5 86	.098	5	.007	.120	1.25
121G12A	2V	IPS	.15	15 5 86	.098	6	.007	.120	1.25

FIGURE 1 – RESULTS OF DEVIATION ANALYSIS ON TYPICAL EQUIPMENT

*** M777 MACHINE HISTORIES ***

MACHINE ID: 131G2A

D M Y	IH IPS	1V IPS	1A IPS	2H IPS	2V IPS	3H IPS	3H BDE
13 5 86	.07	.11	.07	.07	.05	.27	.34
25 4 86	.07	.10	.05	.03	.07	.28	.11
17 3 86	.11	.09	.10	.05	.10	.27	.20
17 12 85	.12	.12	.15	.05	.08	.57	.09
11 10 85	.07	.09	.05	.04	.06	.56	.18

D M Y	4H IPS	4H BDE	4A IPS	PDIS PSI	NOTE MCV
13 5 86	.30	.12	.20	662.00	0 APPEARS NORMAL
25 4 86	.33	.14	.31	660.00	0 APPEARS NORMAL
17 3 86	.25	.10	.20	675.00	0 APPEARS NORMAL
17 12 85	.66	.15	.23	690.00	0 APPEARS NORMAL
11 10 85	.69	.23	.36	750.00	0 APPEARS NORMAL

MACHINE ID: 121G12A

D M Y	IH IPS	2H IPS	NOTE MCV
15 5 86	.23	.15	0 APPEARS NORMAL
30 4 86	.18	.11	0 APPEARS NORMAL
17 3 86	.15	.10	0 APPEARS NORMAL
17 2 86	.12	.09	0 APPEARS NORMAL
22 1 86	.12	.09	0 APPEARS NORMAL
5 12 85	.11	.10	0 APPEARS NORMAL

MACHINE ID: 111G2B

D M Y	IH IPS	IH BDE	IA IPS	2H IPS	2H BDE	3H IPS	3V IPS	4H BDE	PDIS PSI	NOTE MCV
13 3 86	.15	.20	.09	.14	.43	.43	.34	.86	220.00	0 APPEARS NORMAL
14 2 86	.10	.12	.05	.11	.43	.37	.37	.38	220.00	0 APPEARS NORMAL
22 1 86	.09	.23	.05	.10	.63	.36	.43	.54	220.00	0 APPEARS NORMAL
11 11 85	.11	.13	.06	.12	.38	.35	.39	.61	200.00	0 APPEARS NORMAL
6 9 85	.10	.09	.07	.14	.27	.34	.37	.77	220.00	0 APPEARS NORMAL

MACHINE ID: 91G3A

D M Y	1H IPS	1H BDE	2H IPS	2H BDE	3H IPS	3H BDE	PDIS PSI	NOTE MCV
13 5 86	.10	.09	.14	.70	.31	.28	122.00	0 APPEARS NORMAL
13 3 86	.09	.05	.14	.36	.31	.36	120.00	0 APPEARS NORMAL
13 2 86	.09	.05	.10	.43	.27	.31	116.00	0 APPEARS NORMAL
16 1 86	.10	.05	.15	.41	.49	.34	110.00	0 APPEARS NORMAL
29 11 85	.11	.05	.18	.41	.68	.18	110.00	14 LOOSE BOLTS
2 7 85	.10	.02	.20	.40	.36	.20	90.00	0 APPEARS NORMAL

FIGURE 2 – HISTORY ON SELECTED MACHINES

<u>Extending the Method</u>

When it became evident that deviation alarms would enhance the process of fault detection, based on unfiltered vibration in rotating machinery, it was decided to examine extensions. It would seem, for example, that the concept should be applicable to alarms based on machinery spectra as well. But a greater need is in the area of automated fault detection in reciprocating machinery.

Fault detection in power cylinders and compressor cylinders is essentially a problem in pattern recognition. Once the appropriate signal is measured and displayed, we look for:

- the presence of certain events, at the proper location
- the absence of all other events

At present, these results must all be reviewed by a highly skilled specialist. It requires a great deal of experience to determine what is normal for a given situation. Since experienced specialists are not all that common, analysis has been expensive, occasionally impossible, and perhaps even wrong.

If a computer can be used to review patterns and flag anomalies, condition-based maintenance of reciprocating machinery will become a more available and common practice. The experts can concentrate on diagnosis and prognosis rather than wasting their expertise on data collection and on the analysis of data on machines that prove to be good.

Figure 3 shows an example of an “ultrasonic trace” taken on a power cylinder. This curve is the envelope of the acceleration signal contained in the frequency band of about 10 to 30k Hz. Ultrasonic traces are indicative of events in the cylinder; conventional vibration signals are not.

The trace shows bursts of energy along its length. The analyst must be able to determine the causes of those bursts, and whether the events in question are occurring at the right time and whether the amplitude is reasonable. Interpretation of these signatures and detection of problems is partly an art, and one that requires great expertise.

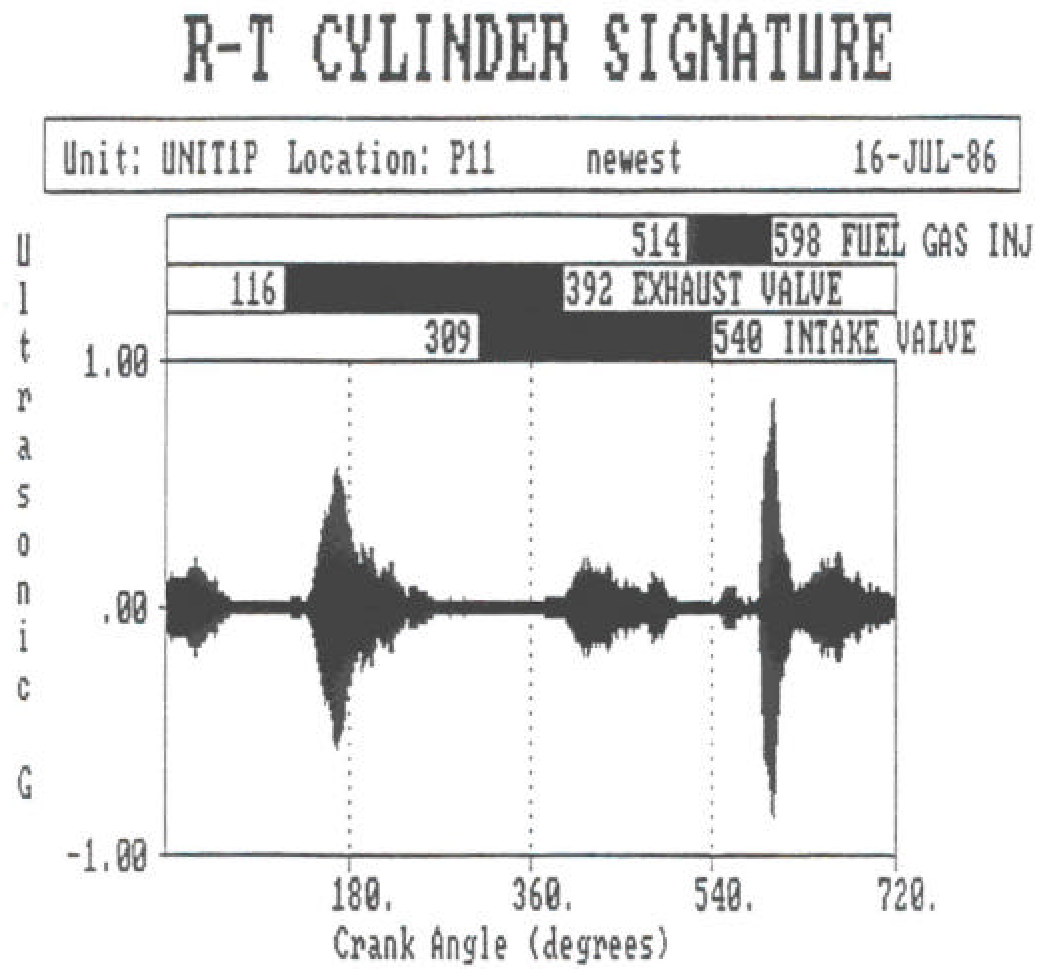

FIGURE 3 – TIMING DIAGRAM & NORMAL ULTRASONIC CURVE

Application to Power Cylinders

Ultrasonic traces were taken from the cylinders of a twelve cylinder, spark ignited engine. It is a two stroke engine with exhaust and scavenging ports and a gas injection valve. The time diagram and a normal ultrasonic curve have been shown in Figure 3.

A computer program was written to calculate mean and standard deviation curves on a degree-by-degree basis by using data from all 12 cylinders. This program could also calculate a limit curve as

Limit = mean + N * standard deviation

where the user selects N.

Figure 4 shows some results for N equal to 1, e.i. for a tolerance of one standard deviation. In the figure, the curve for cylinder 7 is overlaid on the limit curve. Where the cylinder 7 curve exceeds the limit, the area between is shaded.

Two areas of problems were successfully flagged by the deviation alarm process: high blowby due to cylinder liner wear, and wear in the fuel gas valve train. On the other hand, two areas were flagged where there is not really any problem.

Such limit evaluations for all 12 cylinders were compared with the observations of an expert. It was encouraging that most of the problems were detected, but numerous events not representing problems were also flagged.

The study reported here is preliminary in nature. However, the findings appear encouraging.

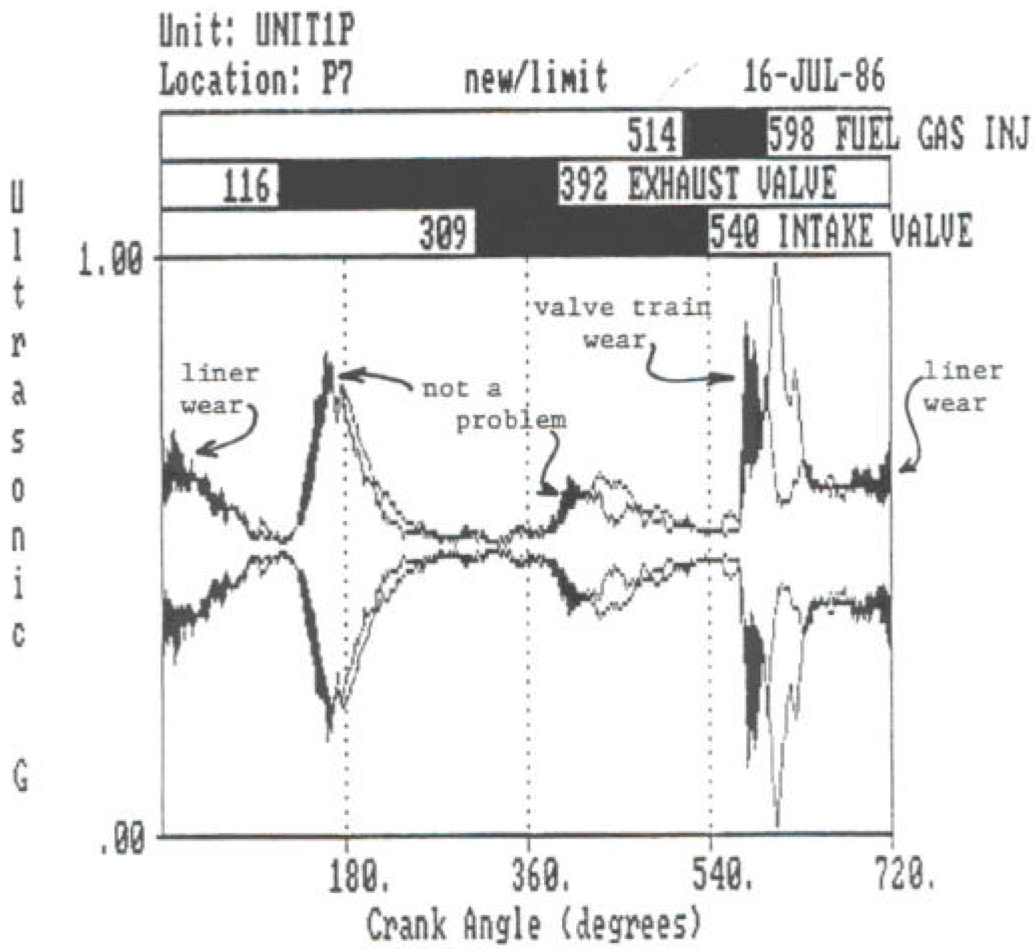

FIGURE 4 – COMPARISON OF CURRENT CURVE WITH LIMIT CURVE

Conclusions

The technique of deviation alarms offers an immediate enhancement to the process of on-condition maintenance of rotating machinery.

The method also holds promise in more demanding applications such as predictive maintenance of reciprocating machinery. More work is required to develop methodology which will result in reliable fault detection without an unacceptable level of false alarms.