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Vibration Signals from Rotating and Reciprocating Machines

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Abstract – Machine condition monitoring is an important part of condition-based maintenance (CBM), which is becoming recognized as the most efficient strategy for carrying out maintenance in a wide variety of industries. Machines were originally 'run to break', which ensured maximum operating time between shutdowns, but meant that breakdowns were occasionally catastrophic, with serious consequences for safety, production loss and repair cost. The first response was 'preventive maintenance', where maintenance is carried out at intervals such that there is a very small likelihood of failure between repairs. However, these results in much greater use of spare parts, as well as more maintenance work than necessary. As mentioned in most machine components give rise to specific vibration signals that characterize them and allow them to be separated from others, as well as distinguishing faulty from healthy condition. The distinguishing features may be because of different repetition frequencies, for example a gear mesh frequency, which characterizes a particular pair of gears, and different sideband spacing's which characterize the modulating effects of the two meshing gears on their common mesh frequency.

Keywords: Vibration, Signals, Rotating, Reciprocating, Machines, Important, Maintenance, Industries, Necessary, etc.

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INTRODUCTION

As mentioned in most machine components give rise to specific vibration signals that characterize them and allow them to be separated from others, as well as distinguishing faulty from healthy condition. The distinguishing features may be because of different repetition frequencies, for example a gear mesh frequency, which characterizes a particular pair of gears, and different sideband spacing's which characterize the modulating effects of the two meshing gears on their common mesh frequency (Antoni and Braun, 2005). Gear-generated signals are usually at harmonics (integer multiples) of the associated shaft rotation speeds, whereas the characteristic frequencies of rolling element bearings are generally not at harmonics of the associated shaft speeds. Some signals, typically associated with fluid flow, such as turbulence or cavitation, have a random nature, but may have a characteristic distribution with frequency. These signals are often 'stationary', that is, their statistical properties do not vary with time, but other random signals, characterized as 'cyclostationary', are often generated by machines and have statistical properties which vary periodically (Polytec, 2010). A typical example is the combustion signal in an internal combustion (IC) engine, where there is a combustion event in each cylinder each cycle (thus happening periodically), but with significant random variations from one cycle to another.

REVIEW OF LITERATURE:

This study thus starts with the various categories into which vibration signals can be divided and thereby classified. The purpose in this paper is mainly to categorize the various signals generated by machine components in healthy and faulty condition, but the type of signal also has a very large influence on the types of signal processing which can and should be applied to them, as described (Vass, *et. al.,* 2008). As mentioned, signals are often distinguished by the repetition frequencies of periodic events and so one of the most fundamental ways of evaluating signals is in terms of their 'frequency spectrum', showing how their constitutive components are distributed with frequency. Mathematically, this is done with various forms of Fourier analysis, as described in great detail, but at this stage it is sufficient to see how the various signal types manifest themselves in the time and frequency domains (Rao, 2005). Some (non-stationary) signals have frequency content which varies with time, and once again this is discussed more rigorously, but at this stage it is sufficient to realize that just as the human ear can recognize changes in frequency patterns with time (e.g. music), such patterns sometimes categorize certain types of machine faults. An example is given by faults in IC engines, where a trained mechanic can distinguish temporally changing frequency patterns resulting from ‘pinging’ and ‘bearing knock’. Many signal processing tools have been developed to try and replicate what can be distinguished by the human ear.

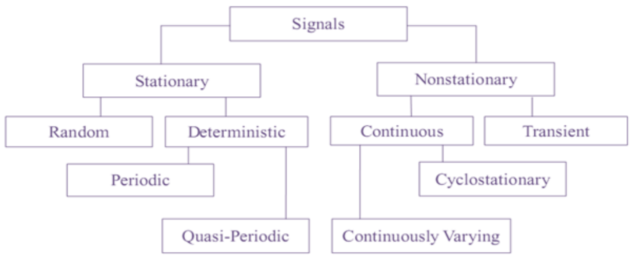

Figure 1 Signal types reproduced permission

Figure 1 shows the basic breakdown into different signal types. The most fundamental division is into stationary and non-stationary, where, as mentioned above, stationary means that the statistical properties are invariant with time. For deterministic signals this basically means that they are composed entirely of discrete frequency sinusoids and thus their frequency spectrum consists of discrete lines at the frequencies of those sinusoids. Once the frequency, amplitude and initial phase (i.e. at time zero) of these components is known, the value of the signal can be predicted at any time in the future or past; hence the term ‘deterministic’. Random signals are somewhat more complex, as their value at any time cannot be predicted, but for stationary random signals their statistical properties are unchanging with time. Individual random signals must be considered as realizations of a ‘random process’, where all realizations vary randomly, but are equally valid (American Petroleum Institute, 2000. Sherwin and Al-Najjar 1999. Childs, 1993). The statistical properties can be obtained by averaging across an ‘ensemble’ of realizations, as illustrated in Figure 2. The conditions for stationarity, for measurements on a machine, are typically that the latter is operating at constant speed and load. If the function being averaged using the expectation operator E [·] is the signal itself, that is $fx(t) = x(t)$, then the result of the average will be the mean value. If $fx(t) = x2(t)$, the result will be the mean square value. One rarely has a large number of realizations of a process and never an infinite number, so it is convenient to be able to perform the averaging along the record. This is valid if the signals are not only stationary but also ‘ergodic’. The fundamental meaning of this is that all realizations are statistically equivalent. The signals depicted in Figure 2 might for example be vibration signals measured on a number of vehicles driven at constant speed around a uniform test track. If the vehicles varied from small cars to large trucks, it is quite possible for the process to be stationary (i.e. the mean value at any time t to be constant), but for it to be ergodic, all the vehicles would have to be of the same type. It is then clear that averages along the record would have equal validity to averages across the ensemble.

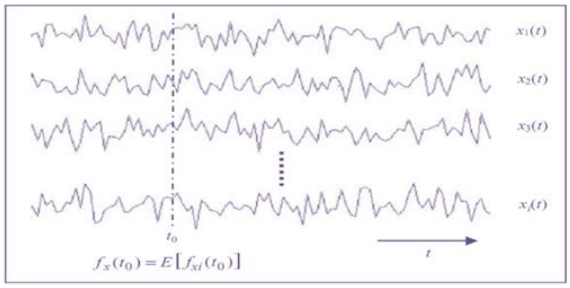

Figure 2 Ensemble averaging reproduced permission

‘Non-stationary’ means anything which does not satisfy the conditions for stationarity and once again it can be divided into two main classes, ‘continuously varying’ and ‘transient’. There is no hard and fast rule for distinguishing between these two types, but in general it can be said that transient signals only exist for a finite length of time and are typically analysed as an entity. Once again, this requires clarification, since a decaying exponential function, for example, theoretically decays to infinity, but in practical terms it only has a measurable value for a finite time. The terms ‘energy’ and ‘power’ are used to distinguish between transient and continuous (stationary or non-stationary) signals (McMillan and Ault, 2008). An analogy can be drawn with electrical signals in a resistive circuit, where the power W = EI, and E and I are the voltage and current, respectively. Since E = IR, where R is the resistance, the power is proportional to the square of the voltage or current, that is W = I 2R = E2/R. Similarly, the true power associated with a vibration signal is related to the square of its amplitude through some sort of impedance or admittance function, and it is common simply to call the squared value the ‘power’. A transient signal has an instantaneous squared value or power at each point in time, but is characterized by the integral of this ‘power’ over its whole length in time, this being called its ‘energy’. A stationary random signal by definition has a constant power and therefore infinite energy. Cyclostationary signals by definition have power (always positive) which varies periodically with time, and so their total energy is also infinite. Other non-stationary signals, such as vibration signals measured during the run-up or coast-down of a machine, also have a finite length, but are more likely to be considered as continually changing non-stationary signals, rather than transients, since they are typically analysed by being divided into short quasi-stationary sections, to see how their power varies with time (time/frequency analysis). Therefore, in this Project a transient will be treated as a signal that is analysed as an entity, with finite energy, and not divided up into shorter sections. Typical examples would be the impulsive force corresponding to a hammer blow, and the impulse response of the structure to which the hammer blow is applied. Continuously varying non-stationary signals will often be treated by the techniques of time/frequency analysis.

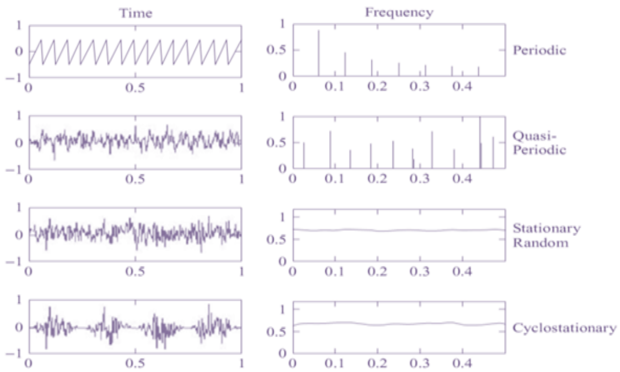

Figure 3 Typical signals in the time and frequency domains

As mentioned above, the different types of signals have different characteristics in the time and frequency domains and these are summarized in Figure 3 for continuous signals (i.e. stationary and cyclostationary).

1- Signals Generated by Rotating Machines:

In condition monitoring, changes in vibration signals are ascribed to changes in condition, so it is important that other factors which cause changes in vibration signals are considerably reduced or eliminated. Vibrations tend to change with the speed and load of a machine, so this section primarily considers the signals generated by a rotating machine operating at constant speed and load, for which the signals will typically be stationary and/or cyclostationary. Occasionally, use can be made of non-stationary signals, such as those generated by a machine under run-up or coast-down conditions, but such signals should be processed with the appropriate analysis techniques, such as the time/frequency techniques treated.

2- Signals Generated by Reciprocating Machines:

This section deals mainly with signals from IC engines, such as diesel and spark ignition engines, but also includes other reciprocating machines such as pumps and compressors. Much more than with rotating machines, the vibration signals from reciprocating machines are a series of responses to impulsive events in the machine cycle, such as combustion, piston slap, bearing knock, valves opening and closing, and so on. The four phases of an IC engine cycle are induction–compression–combustion–exhaust. In a four-stroke engine each of these phases occupies one stroke, or half a revolution, so that a complete cycle is two revolutions and the cyclic frequency is half crankshaft speed. For two-stroke engines, all four phases are achieved in two strokes, or one revolution, so that the cyclic frequency is equal to crankshaft speed. Reciprocating compressors are divided into 'single-acting', where gas is compressed in only one direction of the piston motion, and 'double-acting', where compression is achieved during both forward and backward strokes of the piston. Figure 4 is a cross-section through a gas engine/compressor that will be used to demonstrate the basic concepts of reciprocating machine vibrations. Such a gas engine/compressor, in a 12- or 16-cylinder version, is often used to pump natural gas through pipelines, using some of the gas as fuel. It is a spark ignition engine and, in fact, has two spark plugs in each cylinder for security. Each 'throw' of the crankshaft has two engine pistons in a 'V' arrangement and one compressor piston. Note that the piston rod moves parallel to the cylinder, so as to facilitate double-acting operation, and the compressor connecting rod is connected to the piston rod at a sliding 'crosshead'.

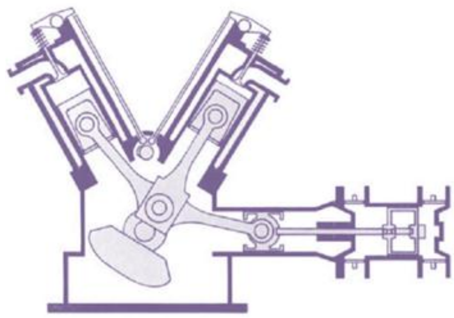

Figure 4 Cross-section through a gas engine/compressor

CONCLUSION:

The study of the damage detection performance for various damage states can be extrapolated for use in industry. The knowledge of which features perform better for certain classes of damage and don't suffer from swapping suggestions can be used for more informed damage classification of damage types. This will allow CBM system to achieve better reliability and performance. The second and most fruitful contribution was the overview of the FMH damage feature for use in detecting worn tooth damage. The results in this study showed the FMH damage to be an excellent candidate for detecting early stages of gear damage. With earlier detection of gear wear, better planning of maintenance and ordering of replacement parts can be achieved. This results in a reduction of cost and increase in potential safety.

FUTURE WORK:

The majority of the damage features performed well under certain conditions while others did not. As such they can be used for group classification of various damage types as well as location in multidimensional data driven analysis. The next step after the work presented in this study would be for the damage features to be compared in a statistically significant way by using groups of features instead of a single one then compared against which type of damage was present.

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