Automated Feature Selection for Embeddable Prognostic and Health Monitoring (PHM) Architectures

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Abstract: **This work presents novel approaches for feature selection and alarm settings that can be exploited by automatic health monitoring systems that use vibrations of industrial machinery as a primary source for detection of failures and incipient faults. For any feature extracted from a sensor signal, a baseline is created that is accepted or rejected according to its statistical properties and the largest time constant of the system. The proposed framework determines alarms using an alarm coefficient that is motivated by established engineering norms, heuristics, and acceleration models. The operation of the architecture and the system performance are tested with industrial failure data.**

I - INTRODUTION

Temperature and vibration are the traditional indicators of health in industrial machinery. Temperature settings are usually well characterized because they are process-related. Alarms set for process-related indicators such as temperature are called design alarms [1] because their settings are determined by the designer. The vibration level of the machine is the result of far more complex mechanisms and is not under the exclusive control of the designer [2]. This type of indicator is referred to in this work as "feature alarm" and is an indirect consequence of the process. Vibration alarm settings traditionally rely on either heuristics or on trial and error. A formal approach can be summarized in engineering norms such as ISO10816, which suggest acceptable levels of vibration according to machinery size and mounting. Norms such as ISO 10816 are recommendations, but in general, the final decision and fine tuning is up to the user. Due to the multivariable and complex nature of the phenomena associated with the vibration signal, there is a lack of standardization in the type of measurement. Commonly used measurement types are acceleration, velocity, and displacement, which are quantified as *features*, such as rms and peak values. More complex indicators or features that can be used, are crest factor, kurtosis. These features may also be extracted from the frequency spectrum of the vibration data, using narrow or wide bandwidth, wavelets, etc. [3-6].

As a result of this problem's complexity, the industry relies on the in-house personnel to determine the appropriate settings for each individual machine. This paper presents an alternative solution that establishes the setting in an automated way and allows embeddability in the Prognostic Health Monitoring system. The architecture discussed is centered in vibration signals, but it is not exclusively for this type of signal since the principles derived through this study hold for other types of signals as well. The proposed system can be embedded in most of current microprocessors used in industrial controls.

II - PROPOSED ARCHITECTURE

The alarm setting is an integral part of the automated architecture proposed (see Figure 1). The vibration signals used in this study typically come from accelerometers. Features or indicators are extracted from these signals in order to determine the condition of the machinery.

III - FEATURE EXTRACTION AND SELECTION

The signals provided from the sensors have to be classified and characterized. There is in the literature vast information about possible metrics and classification methods. Common features are rms, peak value, crest factor, kurtosis, narrow or wide bandwidth frequency features, wavelets among others.

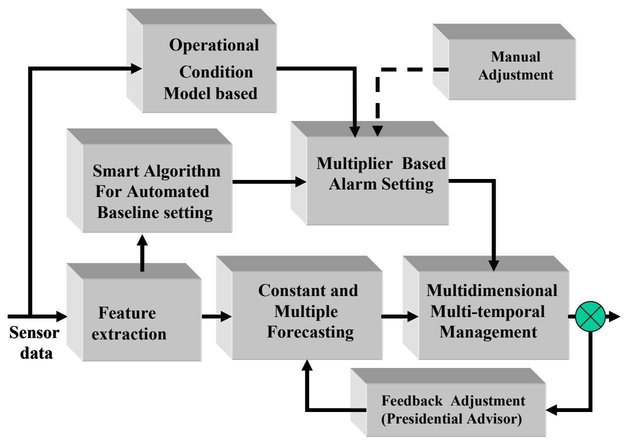

Figure 1. Embeddable PHM Architecture

Good or Acceptable Feature

A good feature or condition indicator is some characteristic or metric that allows making a correct diagnostic and/or good prognosis about the machine's condition. Because a good feature cannot be selected a priori, we use a more practical definition of an "acceptable feature". An "acceptable feature" is an indicator derived from some physical property or variable measured from the machine in a particular operational condition that has relatively little statistical variation for a time longer than the largest time constant involved in the process of a healthy machine. This acceptable feature allows the establishment of a baseline that characterizes the healthy condition of the machine. This method has a drawback that it does not warrant any sensitivity for a particular failure, but its stable behavior under normal operational conditions avoids false-positive alarms in the diagnostic assessment of the machine.

The weakness in the sensitivity to a particular failure that drives to possible false negatives is mitigated by use of a large number of features in the time and frequency domain as candidates to establish acceptable base line.

Feature Space and Computation Resources

A considerable number of acceptable baselines characterizing and monitoring the system for several indicators increase the probability of at least one to be sensitive to a particular failure when the system changes as a consequence of the failure.

Often we face situations where the number or the complexity of the selected features can not be accommodated due to the lack of computational resources inside an embedded system. A compromise is needed in such situations as to the number and types of feature indicators that can be embedded. Often the selection process involves heuristic choices related to the most critical failure modes and most discernable features.

IV - BASELINE SETTING

This work presents a new approach for settings alarms in an automated way. This is done by establishing a candidate baseline for each feature. An acceptable baseline is determined by two parameters: the first is associated with the longest time constant of the system and the second with the statistical properties of the candidate baseline. Based on these two criteria, a feature may be used as a baseline or not.

Criteria based on largest time constant

The largest time constant of the system is related with the size of the machinery and the processes themselves. For large industrial equipment such as large pumps, blowers and centrifuges, 20 minutes is usually a very conservative estimation. In general terms, it is reasonable to establish a time window that is at least three time the largest time constant of the system (see Figure 2). This allows the system to reach at least a quasi-steady state. The response for a step function in the first order system is:

$$f(t) = 1 - e^{-t/\tau} \quad (1)$$

And its slope can be computed as:

$$\frac{\partial f(t)}{\partial t} = \frac{1}{\tau} e^{-k} = m \quad (2)$$

The first criterion for selecting a baseline in mathematical terms is:

$$|m| < 0.05 \quad (3)$$

where m is the slope of the linear regression of the candidate baseline.

Criteria based on statistics (6σ)

This criterion is based on the very low probability, assuming Gaussian distribution, of obtaining a consistence value greater than six time the standard deviation (6σ) (Figure 2). This restriction minimizes the possibility down to very low random probabilities of having a false alarm when the machine is in good operational and health condition.

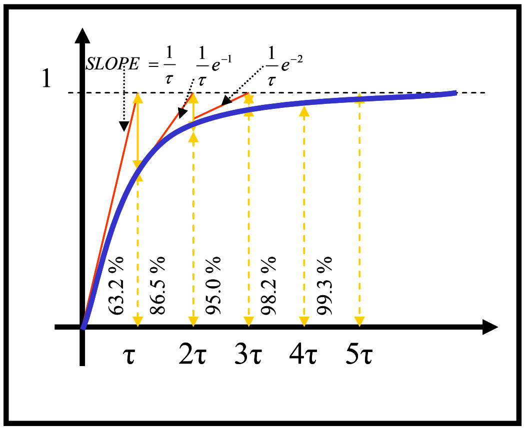

Figure 2. Step response to first order system

Based on this phenomenon, the acceptable baseline has to comply with the following relation:

$$\sigma/\mu < 1/6 \qquad (4)$$

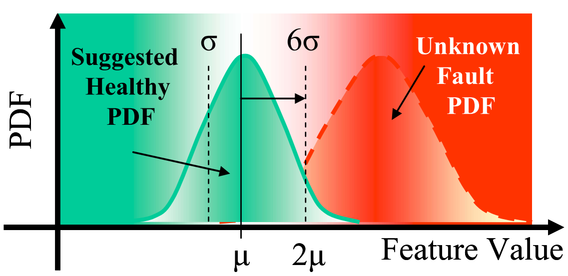

Figure 3. Statistical Criterion

Based on the criteria above, Figure 4 shows examples of acceptable and unacceptable baselines

V – ALARM SETTING

The alarm setting is based on applying an alarm coefficient that is multiplied to the establish baseline. The selection of alarm coefficient is based on five aspects:

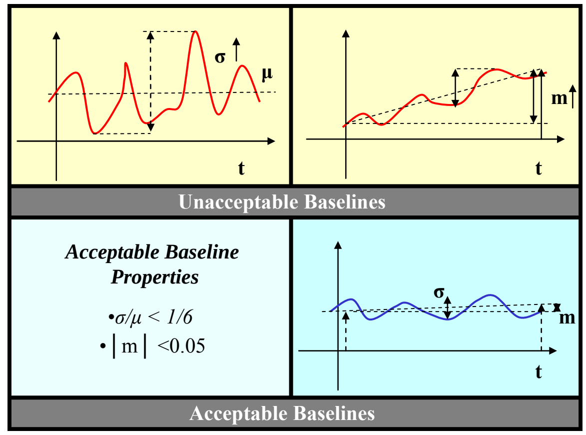

Figure 4. Unacceptable and Acceptable Baselines Examples

- Heuristics
- The presence of a "safety factor" reflected in the norms
- The basic mathematical structure of the acceleration model
- Ratio SD/mean
- Slope(m) of baseline

Heuristics

The Canadian Navy has been using vibration monitoring for decades, and they have established heuristics of 2X [6], that is any signal twice the level of the base line is a source for concern. Monitoring vibration has been a standard practice for power nuclear facilities critical for safe operation. Maxwell presents statistical information in crack propagation over pump shafts [7] (see Figure 5).

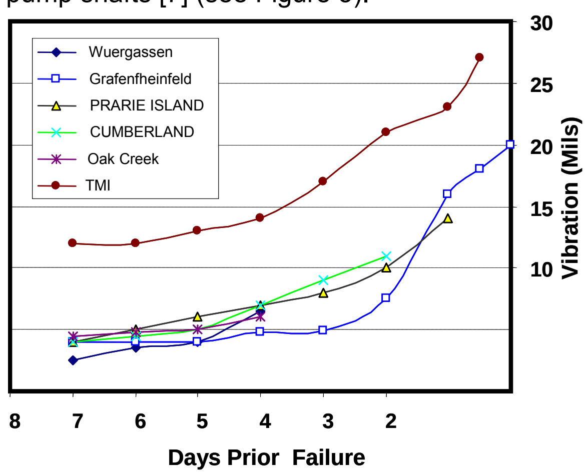

Figure 5. Vibration crack propagation over pump shaft

The ratio observed among the baseline and the final vibration failure was between 2 and 6.

Norms

The ISO 10816 norm suggested different levels of acceptable vibration depending on size and mounting of the machinery. The incremental level from an acceptable to an unaccepted stage is a proportional constant of value of 2.53 independent of the size and mounting (see Table 1) below.

Table: 1 ISO 10816 norm

	Machine		Class I Small Machines (≤15Kw)	Class II Medium Machines (15Kw< ll< 75Kw)	Class III Large Rigid Foundation	Class IV Large Rigid Foundation
	in/s	mm/s				
	0.01	0.28				
V	0.02	0.45				
E	0.03	0.71		GOOD		
L	0.04	1.12				
O	0.07	1.80				
C	0.11	2.80		SATISFACTORY		
I T	0.18	4.50				
Y	0.28	7.10		UNSATISFACTORY		
	0.44	11.2				
R	0.70	18.0				
M	0.71	28.0		UNACCEPTABLE		
S	1.10	45.0				

Acceleration model

Acceleration models of the reduction of life in equipment have been used extensively. Representative examples include Arrhenius for temperature and inverse power law for bearings [1]-[10]. These two models and specifics modification describe almost the complete universe of the acceleration model.

Inverse Power Law Model (IPL)

This is a model that is commonly used to characterize the life of many devices such as capacitors, bearings, insulating fluids and many other components operating under non-thermal stress. Typical examples of non-thermal stress are speed, load, corrosive medium and vibration [9].

$$L(s) = A \cdot \frac{1}{s^n} \quad (5)$$

Where:

L(s) is the life under non-thermal stress *s*
A is an experimental constant
n is an experimental constant

Under a particular stress *s* the probability density function can be estimated using Weibull distribution [1][9][12].

$$f(t,s) = \frac{\beta}{L(s)}\left(\frac{t}{L(s)}\right)^{\beta-1} \cdot e^{-\left[t/L(s)\right]^{\beta}} \quad (6)$$

Where:

t is time (t > 0)
β is an experimental constant independent of the stress level.

The reliability function is then given by:

$$R(t,s) = e^{-\left[t/L(s)\right]^{\beta}} \quad (7)$$

The failure rate is given by:

$$\lambda(t,s) = \frac{f(t,s)}{R(t,s)} = \beta A s^n \left(tAs^n\right)^{1-\beta} \quad (8)$$

The failure rate (λ_A) under accelerated stress (s_A) is:

$$\lambda_A(t,s) = \beta A {s_A}^n \left(tA{s_A}^n\right)^{1-\beta} \quad (9)$$

The failure rate (λ_U) under normal use (s_U) is:

$$\lambda_U(t,s) = \beta A {s_U}^n \left(tA{s_U}^n\right)^{1-\beta} \quad (10)$$

From the definition above, the acceleration factor (AF) can be drived as the indicator of the aging of the component:

$$AF = \frac{L_U}{L_A} = \left(\frac{s_A}{s_U}\right)^n \quad (11)$$

This simple equation can be used as a reference of alarm setting for any stress indicator because it is independent of β which is particular for a process or device.

From equation 11, the stress parameter can be redefined as a feature indicator. The alarm level of the feature (F_{Alarm}) in function of the feature base line (F_{Base}) can be expressed as:

$$F_{Alarm} = F_{Base}\left(\frac{L_U}{L_A}\right)^{\frac{1}{n}} \quad (12)$$

Equation (12) establishes one of the most important conclusions in this work because, assuming the feature indicator is a direct reflection of a stress condition and a reduction in life greater that 90%, the experimental constant *(n)* has a very low influence upon the value of the feature alarm. These results are practically independent of the feature and independent of the device because equation 12 is independent of the experimental shape *(β)* of the Weibull distribution function.

A particular application of inverse power law model for bearings is known as Palmgren's equation [1]. This model has been extensively tested in ball and roller bearings. The Palmgren's equation provides the relation between the load and the 10th percentile L_{10} of the life distribution of the bearing.

$$L_{10} = \left(\frac{C}{F}\right)^{\alpha} \frac{10^6}{rpm} \qquad (13)$$

Where:

F = load of stress

C = constant depending on the bearing geometrical characteristics.

α = is the inverse of the experimental value (1/n)

For a bearing, the β shape factor of the Weibull distribution ranges typically from 1.1 to 1.5. The α coefficient typically is 3 for ball bearings and 10/3 for rolling bearing [1]. Figure 6 shows how, regardless of the type of bearing (α: 3 to 5), an effective reduction of life due to increases in stress (or in this case vibration) is bounded between 1.5-3 [1][10].

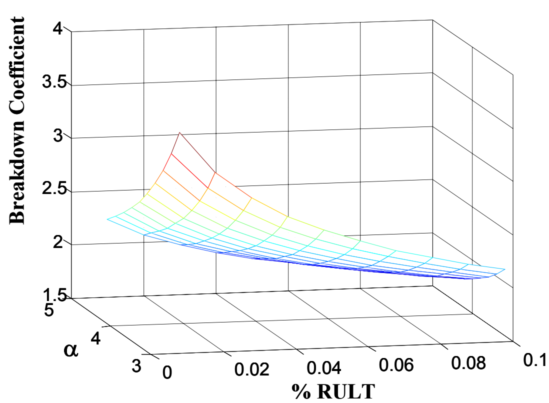

Figure 6 Power law acceleration model and reduction in Life

The Arrhenius Model: This model represents degradation in the structure/material as a function of the temperature. It has been applied in electrical insulation, semiconductor materials, battery cells, lubricants, plastics, and incandescent lamp filaments among other things [1].

$$L(T) = A \cdot e^{\frac{E}{kT}} \qquad (14)$$

Where:

L(T) is the life under thermal conditions

A is experimental constant

E is activation energy

T is temperature in Kelvin

k is Boltzmann's constant $8.6171.10^{-5}$ eV /^{o}C

For temperature alarm settings, similar derivation to those developed for inverse power laws can be done, but alarm setting in temperature is well understood because it is usually related to the design.

The temperature alarm (T_A) expressed as a function of the temperature of design or usage is (T_U):

$$T_A = \frac{T_U}{1 - T_U \frac{k}{E} \ln\left(\frac{L_U}{L_A}\right)} \qquad (15)$$

Where the value of the activation energy ranges generally from 0.3 to 1.5 eV. Equation (15) shows a greater sensibility to variation in temperature than the IPL stress variation.

Using parameters to establish acceptable baselines, the bounded limit derived from acceleration model, norms, and heuristic knowledge, the following table of alarm coefficients is proposed.

Table2: Alarm Coefficients

	σ/μ < 0.042	σ/μ < 0.082	σ/μ < 0.167
m < 0.007	2	3	4
m < 0.018	3	4	5
m < 0.05	4	5	5

Figure 7 summarizes in schematic ways the alarm settings proposed in this work.

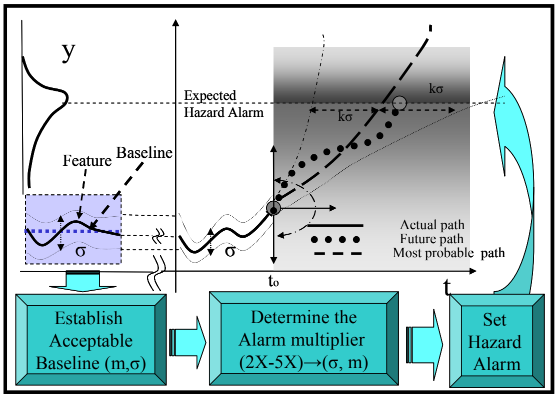

Figure 7. Diagram of the automted setting Alarm

VI - DECISION LOGIC: DIAGNOSTIC AND PROGNOSTIC

The decision module consists of projections for three temporal stages in order to track changes in vibration over a period of hours, days and weeks. The projection or prognosis is fused with the result of the automated alarm setting of the accepted baseline. This two-dimensional approach not only takes into account the current levels of feature values but also their rate of change. The prediction algorithms can be implemented by embeddable low-cost algorithms, for example by using linear weighted regression. Linear or quadratic projection algorithms are selected depending upon which had the least error in the last round of prediction. The system is called a *presidential advisor* [13] and presents a viable solution to prognostics in embeddable systems. The output of the system is summarized in three numerical color codes corresponding to the following conditions; (1) green indicates a normal condition where no part change or maintenance is required at the present time; (2) yellow indicates an initial degrading condition that will demand a maintenance task when it moves to the red; (3) red flag indicates significantly elevated level of concern that normally prompts for stopping the machine immediately.

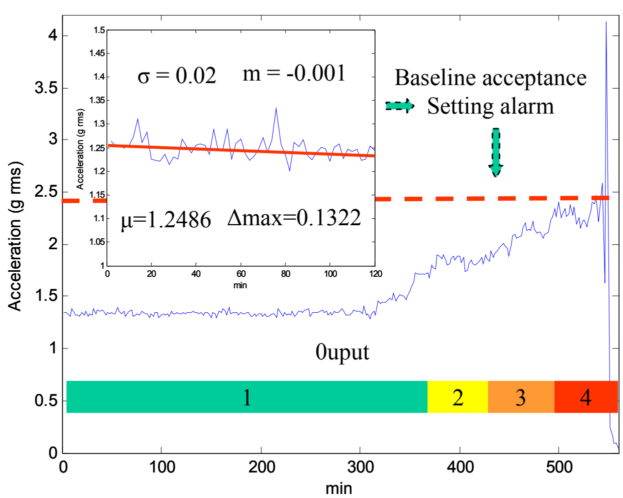

Figure 8. Alarm setting and failure data

VII - RESULTS

Figure 8 presents an example in which the baseline and the alarm system are based on the failure data corresponding to a catastrophic failure that occurred in the main induction motor of a centrifuge. The failure initiated in one of the bearings of a 250 Hp induction motor, which resulted in total destruction of the motor. The destruction on the winding produced a short circuit triggering the protection that stopped the machine. The temperature and vibration sensor alarms failed to trigger for this machine. The data shows the rms feature of the accelerometer signal, sampled at 10 KHz for 0.4 s every 2 minutes. The baseline is accepted and set at a value of 1.24. The alarm is then set to 2.48 in accordance to Table 2. As the fault progresses for a period of time, the alarm changes in the proposed architecture to different levels.

VIII - CONCLUSION

A complete methodology with analytical support is proposed that establishes baseline and alarms. The methodology is developed under the assumption that the feature indicators are reflecting the stresses in the machine and should therefore be ruled by the same mathematical model that rules the reduction of life under stress. The methodology is intrinsically strong against false-alarms but is weak in warranting sensibility to a particular problem (false negative). This weakness is addressed by testing a large number of feature-baseline candidates, thereby increasing the possibility that at least one becomes a failure indicator. The hierarchical structure and simplicity of the proposed methodology allows for easy portability into embeddable monitoring systems. Its general efficacy remains to be proven for a wider range of fault data.

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