Information from Centralized Database to Support Local Calculations in Condition Monitoring

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Abstract

Maintenance in industry is currently moving from time planned preventive methods to condition-based operation for better process reliability and lowered manufacturing costs. Machine vibrations include information from operating state and machine health and can be used in the computing of several different features for condition monitoring and process control. These describing values can be used for the estimation of remaining useful life (RUL). Local computing enables the use of advanced algorithms for dense vibration data on-site, right next to the monitored process so that the data can be turned into information without the need for large data transfers and centralized computing. Calculated features can be supported with other sensory data, information through expert knowledge, modelling, and data from similar systems in other installations. Developments in wireless technologies enable the use of small nodes in distributed computing. This paper examines the use of locally calculated generalized norms in combination with supporting information from the global maintenance database.

Keywords: intelligent indices, local calculation, edge computing, vibration measurements, generalized norms, combined information

1 Introduction

It has been studied that a large part of the total operating costs in all manufacturing and production plants can consist of maintenance costs. Industry related maintenance costs can vary from 15 percent in food industries to 60 percent in heavy industries of the cost of goods produced. (Mobley, 2002)

This paper introduces advantages of using combined information from several similar targets in addition to just monitor a single target separately. These systems or machines can be located at the same site or at any other location that fits into predetermined criteria. Systems that can be classified to operate in comparable environments make the base for the possible measurement locations. After classification parameters are met for the locations, the valid measurement points can be formed only when the operating parameters for the machinery in these systems match. After all the criteria for valid points are met, these values can be used to improve condition monitoring performance in individual locations. Measurements can be collected along with the meta-data determining measurement conditions and operating parameters and sent to a centralized condition monitoring database. This database provides supporting information to all relevant operators. Information from the database helps in the determining of the threshold level for the amount of stress one machine can withstand, locating different fault characteristics, and improving operating performance through best practices. The determining of the threshold level for machine stress resistance gives the life expectancy for the part and the variation of the measurement points shows the reliability of these results. Operating habits vary between different sites and even within the same site. This framework could include the effects of these different driving habits and reveal the best practices quickly.

Vibration measurements are widely used in industrial applications to monitor condition and operating state of the machinery. Almost all machines vibrate and when the machine operation changes, the vibrations change as well. These changes can indicate shift in machine condition when linked to specific faults. Predicting developing faults leads to minimal down time and better overall control of process maintenance with scheduling and preventing of sudden break downs.(Rao, 1996)

Local calculation enables the use of vast amount of data in condition monitoring and machine control. Advanced feature extraction can be done in small computers located next to the monitored machinery or in the sensor itself. Informative indices extracted from the dense accelerometer data should be used as any other measured data. The applications include long term condition monitoring and determining of remaining useful life that enables the prognostics aspect and real-time operating state detection. These values can be used in control applications, stress monitoring or calculating of condition indices when the machine is operating in the predefined reference state.

Centralized database in a server with versatile interface enables the use of this data in several different locations by varying users at the factory. This local database can be connected to a global framework providing interoperability and integrability of services (Arrowhead). This work is done in Arrowhead project which develops widely interoperable and integrable service-based collaborative automation framework. Its vision is to enable collaborative automation by networked embedded devices and lead the way to further standardization work. In the following section, short style guidelines are given.

2 Local Calculation

Advances in technology have made the processing of large datasets with small distributed systems possible. Data acquisition (DAQ) system combined with the field programmable gate array (FPGA) can do the data processing while recording it (Shome et al., 2012; Zheng et al., 2014). FPGA core can be faster in certain calculations than comparable digital signal processors (DSPs) and personal computers (PCs) (Vite-Frias et al., 2005). It can be useful e.g. in data pre-processing where it can filter the noise from the vibration signal in real-time (Shome et al., 2012). Small programmable automation controllers (PACs) can be very useful at the algorithm development phase as they can record varying sensory data streams and run calculations for the data. Figure 1 presents the algorithm development for local calculation and generalized third party data usage. The PAC setup that we have used for vibration monitoring cases consists of National Instruments cRIO-9024 controller with cRIO-9114 chassis which has Xilinx Virtex-5 reconfigurable FPGA core. Vibration sensors were connected to NI 9234 analog input module with built in anti-aliasing filter designed for the vibration measurements. Code for data acquisition was developed with Labview software. cRIO can act as a versatile platform for algorithm development for its modular construction and easy configuration.

Determination of the machine state based on vibrations makes efficient maintenance planning possible through predictions of developing machinery condition. It can be also used for planning of machine use in order to prolong its operational time if there is e.g. planned maintenance break coming up.

Vibration data can be used for the automatic maintenance operations. Nowadays, spare parts dealer gets alarm when certain threshold is exceeded and he can react immediately and start necessary preparations for sending replacement parts or planning of repair operation. Data send to third parties from the plantwide database should be carefully secured and only intended parties should have access to this information. Data should be carefully defined with relevant metadata especially for third party users since values without any connection become obsolete. Automation service providers have applications using this presented fast maintenance idea. ABB has a rapid response service (Rapid Response) that promise to provide instant repairs and needed spare parts in an agreed timeframe. They use data from clients machinery to monitor exceptional situations or failures and minimize the process down time. This idea can be further developed by the use of local processing for advanced monitoring methods.

Wireless technologies enable interesting applications for these small devices capable in signal processing. These nodes are capable in data compression and transferring of large amounts of data wirelessly (Huang et al., 2015), data filtering (Ramachandran et al., 2014), and certain transformations (Merendino et al., 2011). Unfortunately nodes have restrictions in measurement accuracy and computing power due to limited battery power and the expectation for the low unit cost. Small sensor nodes can have simple algorithms implemented for filtering or pattern recognition but more complex algorithms would require more processing and thereby more battery power (Ramachandran et al., 2014).

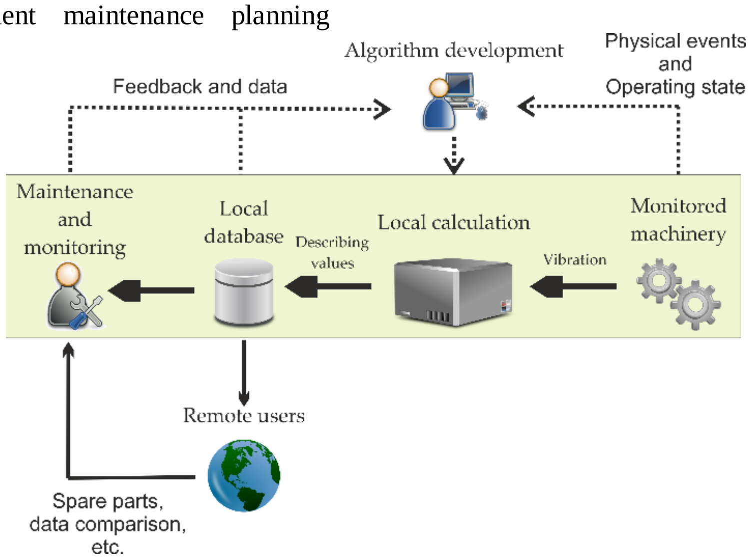

Figure 1. Algorithm development for local calculation and generalized use of extracted features.

In both cases, data transfer of raw measurement data is usually unnecessary and would require high bandwidth. Additionally, in case of wireless sensors the use of energy due to unnecessary data transfer should be avoided (Lahdelma and Juuso, 2011a). Guo and Tse listed several references to available compression methods in (Guo and Tse, 2013) for applications where lots of vibration data needs to be transferred. Huang et al. presented a lossless compression scheme for the wireless sensor network and achieved the average compression ratio of 59.01% (Huang et al., 2015).

3 Signal Processing

Vibration signals can be used in measuring simple vibration severity defined by default as the maximum rms value of the vibration velocities. Peak and rms values are just two common features used in vibration analysis. Vibration signal provides large amount of information and different features indicate different processes in machine operation. Finding the right feature for the wanted event is a matter of referencing the calculated values to machine operation and finding the correlations between these values. Features can be combined to form combined indices which in some cases increase the sensitivity of event detection. Generalized norms can be calculated from the vibration data and used to form intelligent indices using nonlinear scaling.

3.1 Generalized Norms

Vibration data has large amount of information which needs efficient processing. Advanced feature extraction methods can describe large amount of measurement points with one informative value. Generalized norms are described as,

$$\left\|\overline{\chi}^{(\propto)}\right\|_p = \left(\frac{1}{N}\sum_{i=1}^{N}\left|x_i^{(\propto)}\right|^p\right)^{\frac{1}{p}} = \left\|\overline{\chi}^{(\propto)}\right\|_{p,\frac{1}{N}} \quad (1)$$

where, $\alpha \in \Re$ is the order of derivation, $p \quad (1 \leq p < \infty)$ is the order of the generalized norm, $N = \tau N_s$ where N_s is the sampling frequency τ is the sample time. Generalized norm is also known as Hölder mean or power mean and it has the same dimensions as the corresponding signal $x^{(\alpha)}$. Some special cases of the norm (1) are arithmetic mean (p = 1), rms (p = 2), and peak value (p = ∞). (Lahdelma and Juuso, 2008a)

Norm calculation compresses five second vibration information of 128000 measurement values (25600 Hz sampling rate) into a single value. Calculation can select e.g. the biggest norm value out of five consecutive values using a sliding window.

Fault detection of fast impact like events can be increased by using derivation of acceleration signal (Lahdelma and Juuso, 2011a). Fault detection has traditionally used displacement $x^{(0)}$, velocity $x^{(1)}$, and acceleration $x^{(2)}$ signals. Higher order derivatives $x^{(3)}$ and $x^{(4)}$ have been previously used in the cavitation detection of Kaplan water turbine (Lahdelma and Juuso, 2008b). Higher order derivatives extend the range of event detection and by selecting correct signal and norm combination, these values can be used widely in different applications (Lahdelma and Juuso, 2011b). Analogue differentiators/integrators can aid in real time calculations (Juuso and Lahdelma, 2006; Lahdelma, 1992, 1995).

Noise from motors and several other mechanisms occurring simultaneously with the monitored property causes false state detection and errors in values. It is important to filter this noise generated by not desired mechanisms before values are calculated. Sensor placing is comparable to the importance of sampling method in manual sampling measurements. Selecting the right order of norms or combination of norms and using high-pass and low-pass filters can be sufficient in most cases. Using of displacement, velocity, or higher order derivatives according to character of the monitored process improves the feature extraction. Different norm values can also be combined to make some events more visible.

3.2 Stress Indices

Stress indices are formed from calculated norms by the means of nonlinear scaling. Norm values are scaled to the linguistic range of [-2, 2] for easy understanding. These scaled values are easy to comprehend and user without deeper understanding about certain measurement from the process can easily use this linguistic range which translates to {*very low, low, normal, high, very high*}. These scaled values can be used in decision making and control like any regular process measurements. (Juuso, 2004, 2011a)

Stress indices can reveal sudden high stress areas in machine operation and guide the machine operator or change the customary habits of machine operating cycle. Indices can reveal the remaining useful life (RUL) of the monitored component by summing up indices from more severe vibrations that exceed certain threshold limit. RUL can be estimated when the stress resistance of certain studied part is known. This information can be achieved through monitoring of the part from installation to break down. Figure 2 presents the stress indices and their use in the describing of sudden and cumulative stress.

Stress causes fatigue, which forms micro fractures. This micro fracturing can be seen as rise in the level of stress indices. Indices are scaled according to the current condition of monitored part and the scaling function needs to be updated after the fatigue have caused changes in condition as the old range is no longer valid.

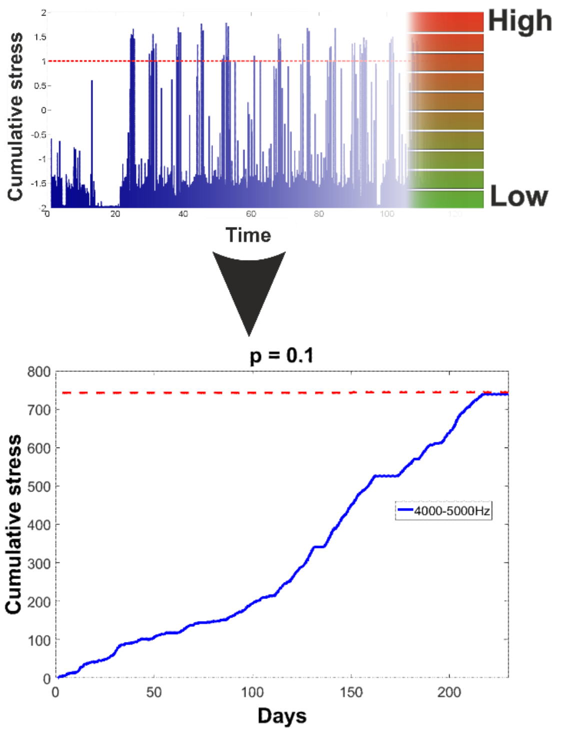

Figure 2. Stress indices scaled to linguistic levels and used to form cumulative stress.

New values can be included in calculations according to changed state and the order of the norms can be re-evaluated if needed.(Juuso, 2011b) Cumulative stress is formed by adding the indices exceeding the threshold level of high stress. Linear increase in cumulative stress indicates that the stress cycles are relatively similar and there have not been any dramatic changes in condition. After the material has experienced enough high load cycles, the micro fractures formed by the stress change the vibration levels and this can be seen as increased slope in cumulative stress meaning that there are more indices exceeding the threshold level for the high stress.

3.3 Measurement Index

Norm values can be used also to track relative changes over time in comparable situations with dimensionless measurement index (MIT). (Lahdelma, 1992) This index has been used in rating of the machinery condition and it is defined as,

$$ {}^{\tau}MIT^{p_1,\dots,p_n}_{\alpha_1,\dots,\alpha_n} = \frac{1}{n}\sum_{i=1}^{n} b_{\propto_i} \frac{\left\|\overline{x}^{(\propto_i)}\right\|_{p_i}}{\left(\left\|\overline{x}^{(\propto_i)}\right\|_{p_i}\right)_0} \tag{2} $$

where norms $\|x^{(\alpha i)}\|_{pi}$ are obtained from the signals $x^{(\alpha i)} = 1,\dots,n$. The divider represents the state where the machine is in normal operational state, $b_{\alpha i}$ is a weight factor for rating individual faults or events. The sum $\Sigma^{n}_{i=1} b_{\alpha i}=n$ can be combined with other quantities like temperature, pressure, or some statistical features of signals.

Figure 3 presents the use of condition indices in condition monitoring of the load haul dumper front axle. The change in condition can be seen as a strong raise in index level after 250 days.

4 Advanced Wear Monitoring

Remaining useful life can be quite simple to predict if the quality of the monitored parts is similar and the stress constant. Known stress resistance level gives the target value for the probable failure limit and this can be used to predict the expected lifetime rather accurately even without monitoring. The more common case is that the stress levels vary and we need to monitor some

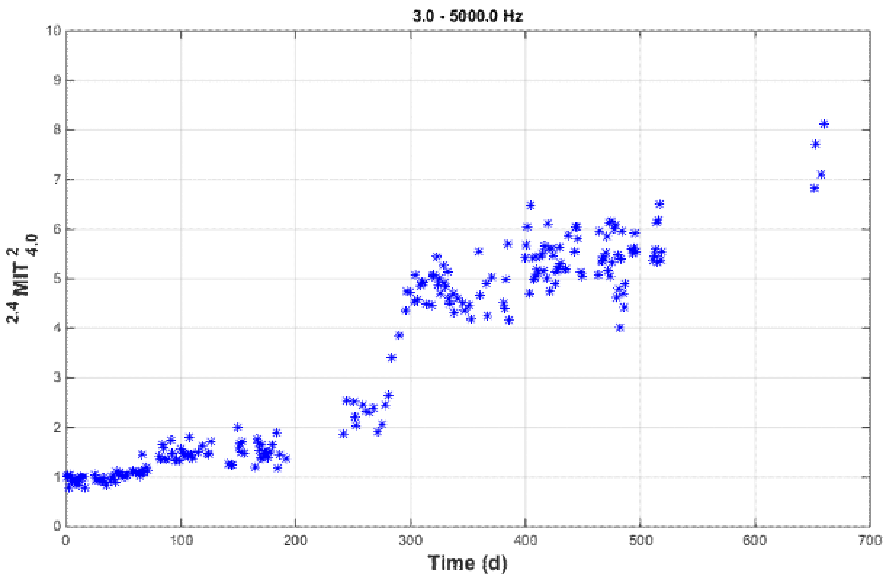

Figure 3. MIT condition indices used in load haul dumper front axle monitoring. (Nissilä et al., 2014)

indicators that tell us about the changes in condition or upcoming failure.

Vibration is a good indicator with rotating or cyclic machinery. The problem here is that the vibrations consist of information from several different mechanisms and we need to filter the data in order to find the valid information. Intelligent indices can isolate the wanted mechanisms of machine operation. These features can then be further used in combination with other indicators in order to strengthen the observations. Increased vibrations with particles in oil or increased temperature can indicate the upcoming failure and this idea can be used with information acquired from other identical setups that have been monitored with similar equipment.

Fault development processes are typically very slow and require long condition monitoring periods. Stress and condition indices require all the information from the installation of new part until the break down occurs to gather the information about the threshold level the part can withstand. This sets high requirements for the monitoring equipment as the locations are not clean and the possibility for cable break or some other failure is high. Single fault gives the data from a single break down and if we want to increase the statistical reliability of the results we need several measurement points. Variation in the results of similar faults gives the probability of break down after certain amount of stress. Characteristics in machine operation and condition monitoring data leading to identified fault can be recorded. Recorded data is now found under this identified fault for building knowledge for the future condition monitoring at all connected sites. Shared condition and stress data makes the determining of RUL more reliable in comparison to monitoring one target alone. It gives various points where the fault has occurred and variation between these points can be used to define probability for the break down if the operation is continued at the same level of stress.

Global condition monitoring database could include the condition information gained with varying algorithms. This requires the scaling of these values into the same universal range (like nonlinear scaling in the forming of stress indices). The database has to use a standardized way of describing data points. Universal descriptions ensure the robustness of the platform and verifies that we are dealing with the right dataset. The database can use a standardized metadata format for making the data exchange as robust as possible. The Open System Architecture for Condition Based Maintenance (OSA-CBM) standardized database of the Machine Information Management Open Systems Alliance (Mimosa) can work as a model for meta-data as it has standardized definitions which help to locate the wanted sensor from the specified machine in certain location (Sreenuch et al., 2013;MIMOSA).

General problem in using shared databases between several operators is the integration to varying systems. Several different clients and languages normally need some proprietary middleware like an application server. Representational State Transfer (REST) uses HTTP methods to transmit data over a wide range of clients written in different languages without the middleware. RESTful API provide data in standardized form according to your data model in flexible way to several different applications. This ensures that all the different operators can use their systems to use the data and provide their own without unnecessary and time consuming changes.(Rodriguez, 2008)

Local signal processing is a vital part in making condition monitoring data into usable form. The database cannot include all the vibration data from every monitored target since the amount of data would be overwhelming and the requirements for the data transfer would be too much. Instead it is reasonable to use feature extraction methods to describe the vibrations with more sparsely recorded values. Figure 2 describes the data reduction that can be achieved by using these feature extraction methods when single describing value is extracted from 5 seconds of raw rod mill vibration data. Raw data is useful to have from situations where machine is working outside of the determined operating state or from some other exceptional situations. This can be done by using triggering for data recording and only save the raw data from exceptional situations since the occasional larger data amounts are not difficult to store.

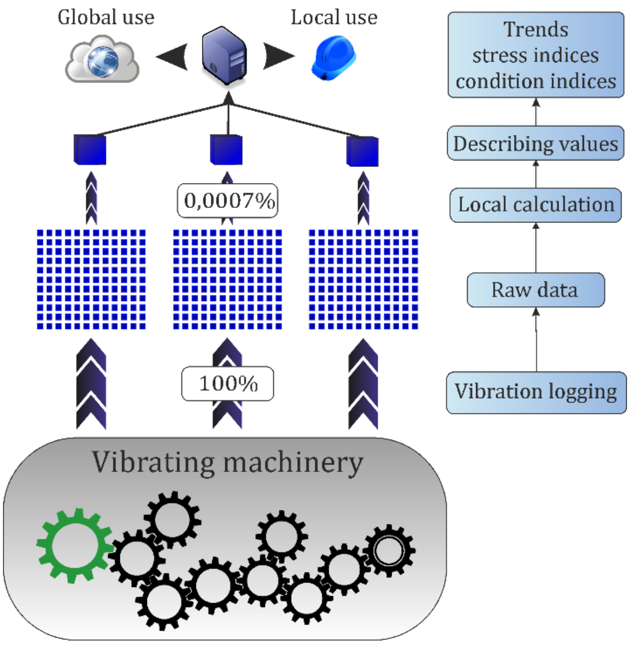

Figure 2. Local calculation in condition monitoring. Data reduction percentages are taken from the calculations done for the acceleration sensor data from rod mill at the Outokumpu Chrome Oy, Kemi mine enrichment plant.

Database information can be used for forming probabilities to back up the local measurements and indices. They can additionally form different statistical indicators that can be scaled to similar range as the local indices. These additional indices could work like other local measurements from the same machine and give more information to decision making process and maintenance planning. The condition monitoring framework could also act as a gateway to share information about the machine operation and faults. This information sharing could aid the machine and part manufacturers. Manufacturers could shorten the response time to develop more suitable products for specific uses or environments.

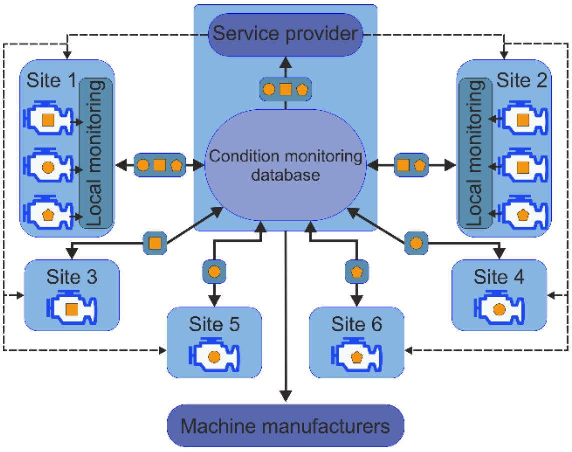

Figure 3. Data sharing with centralized database. Service provider can be e.g. some automation service provider. Orange shapes describe the characteristics of the data.

This idea is not limited to one possible construction only. Figure 5 illustrates the possible framework. Data is defined by its meta-data and data can only be used by the users with privileges so that the data has the pack of users it concerns. Proper certification is needed for this. Maintenance plan of the operator defines its role in this framework. Operator can be both the data provider and the consumer in the case where the monitoring is done at the manufacturing site. Monitoring and analytics can be additionally done by a third party service provider which uses data to develop the operation and to organize maintenance actions. Third party service providers like automation companies have great capabilities to use this data efficiently in their services. The framework would provide important information for the asset lifecycle management and it can help in determining the effects of different factors to asset lifecycle. These effects would also give new ideas to part manufacturers and companies providing machinery.

The Arrowhead framework developed in Arrowhead project can work as a base between different operators sharing their condition monitoring data. The Arrowhead framework is widely interoperable and integrable service-based collaborative automation framework. It visions to enable collaborative automation by networked embedded devices and lead the way for further standardization work. This would enable the service exchange between any actors in the global network. (Arrowhead)

5 Conclusions

Local computing is an effective tool for extracting information from machinery and parts that were earlier impossible due to computational requirements. Localized processing power is relatively cheap in comparison with the savings it can generate through lower down time and improvements in process control. It is inefficient to transfer all the measured raw data to be processed centrally and local computing transforms the data in universally useful and understandable numbers.

The proposed framework takes this locally preprocessed information and makes it useful for several actors. Other operators would benefit from increased information from their processing equipment. Automation and analytics providers could use the information to create new services and add new value to their existing ones. Processing equipment manufacturers would also benefit from increased knowledge about how their products perform at different conditions. Open framework between these operators would enable sustainable development and versatile use of data in several different systems. This is a preliminary work and continuation work includes testing of this idea in practice as a pilot. It also requires further studying in order to find the practical and sound implementation methods.

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