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On-site calculations of generalised norms for maintenance and operational monitoring

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Abstract:

Maintenance in industry and specifically mining industry is currently moving from time planned preventive to condition-based operation. Modern monitoring methods make prognostics and the calculating of remaining useful life (RUL) possible for predictive maintenance. Increased computational power in small programmable controllers and sensors open new possibilities for the efficient on-site calculations. Programmable automation controllers (PACs) make the algorithm testing efficient since the software can be updated easily and measurement setup is customisable. The reliability of wireless technologies is improving and enabling the effortless use of measurement data efficiently where it is needed most. Acquired data can be processed with advanced feature extraction methods before it is transferred onwards, minimising the need for wireless transfer capacity and storage space. If raw measurement data needs to be transmitted, the data can be compressed with a suitable method. The same signals can be used for maintenance and in the controlling of machine operation. This paper introduces several aspects connected to on-site calculations and presents a method for extracting meaningful numbers from high frequency vibration data.

Keywords: Signal processing, generalised norms, on-site calculation, vibration analysis

1. INTRODUCTION

Maintenance has great impact on the efficiency of the business. Emphasis has been on corrective and later in preventive maintenance and currently, steps from time planned to condition-based maintenance are active (Juuso & Lahdelma, 2013). The effective condition monitoring requires the right approach for the specific case by selecting the right sensor. Vibration is a good way to study machine condition because almost all machines vibrate and these vibrations can be linked to specific faults. Vibration monitoring has been accepted to be one of the most powerful methods for diagnosing and preventing machinery faults. Effective maintenance relies on predicting developing faults. Early detection enables the diagnosis of situation and gives time for decision making. Predictive maintenance helps in minimizing the financial impact by preventing break downs and enabling the planning of the maintenance schedule according to machinery condition. (Rao, 1996)

Possibility to acquire huge amount of measurement data enables the use of advanced feature extraction methods for maintenance and operational monitoring. It also raises the requirements for the measurement and analysis devices. Previously the automatic processing of huge amount of process data on small computers was a great barrier but today the increased computational power on modern computers makes the fast analysing of this high frequency data possible. DAQ system with the field programmable gate array (FPGA) can process the data while it is being recorded (Shome et al. 2012) (Zheng et al., 2014). Vite-Frias et al. (2005) presented an FPGA based online spectral computation: the FFT core is cheap, uses low resources and is faster than comparable digital signal processors (DSPs) and personal computers (PCs).

Continuous condition monitoring can use algorithms that are adjusted for the specific case. The development and adjustment of these algorithms need feedback and linking of calculated values to physical events (Fig. 1). After the operation of the algorithm is verified, its results can be used in decision making for maintenance and controlling of machine operation. Values can be made available outside the local operating area for example for early spare part delivery to minimise the down time. Depending on the case, these values can also have other uses in statistics or development purposes. The development state can include the collecting of long periods of measurement data. After the analysis of this data and feature extraction, the algorithm can be implemented into localised logic which handles the calculations and sends meaningful numbers onward. Algorithm can also be adjusted according to changed condition.

Wireless technology makes possible the transferring of data to maintenance crew or machine operators. Underground locations rise new challenges for wireless data transfer. However, this topic is widely acknowledged and being studied. Modelling is used in the characterising of wireless channels in underground mines (Farjow et al. 2014). Data compression can reduce data transferring and storage costs of historian data. The compression method must be carefully examined for its suitability in the particular case. The compression method must be selected according to data usage if the original signal is not recoverable. (Thornill et al., 2004)

Wireless sensors and sensor networks are widely studied technological areas. Increased processing power and advances in mobile technologies have made possible the implementation of some algorithms into these nodes. Nodes can have data compression for sending large amounts of data wirelessly (Huang et al., 2015), filtering of the data (Karuppiah et al., 2014), or certain transformations (Merendino et al., 2011). Nodes have restrictions in measurement accuracy and computing power because of limited battery power and the expectation for the low unit cost.

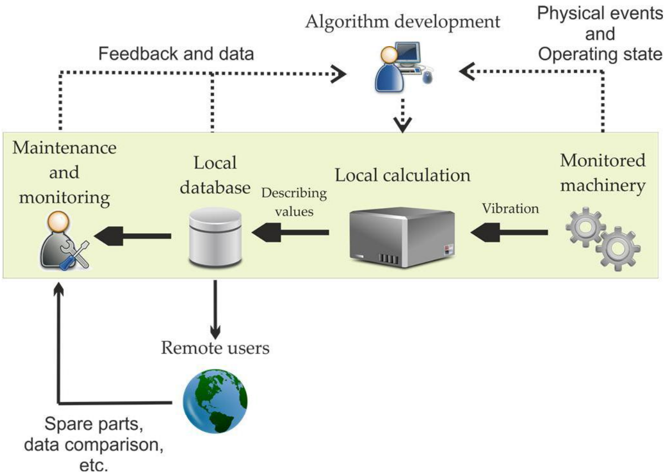

Fig. 1. Development of local calculation for maintenance and monitoring.

This paper introduces several aspects connected to on-site calculations and presents a method for extracting meaningful numbers from high frequency vibration data.

2. GENERALISED NORMS

Advanced feature extraction methods are good for describing the large sets of measurement points with one meaningful number. This paper uses the generalised norms

$$\|{}^{\tau}M_{\alpha}^{p}\| = \left({}^{\tau}M_{\alpha}^{p}\right)^{1/p} = \left(\frac{1}{N}\sum_{i=1}^{N}\left|x_i^{(\alpha)}\right|^{p}\right)^{1/p}, \qquad (1)$$

where, $\alpha \in \Re$ is the order of derivation, p $(1 \leq p < \infty)$ is the order of the generalised norm, τ is the sample time, and $N = \tau N_s$ where N_s is the sampling frequency. The norm $\|{}^{\tau}M_{\alpha}^{p}\|$, also known as Hölder mean or power mean, has same dimensions as the corresponding signal $x^{(\alpha)}$. Some special cases of (1) are arithmetic mean ($p = 1$), root-mean-square (rms) ($p = 2$), and peak value ($p = \infty$). Rms and peak values are often used in condition monitoring. (Lahdelma & Juuso, 2008b)

The generalised norms are efficient methods for on-site data processing as they work well with high frequency vibration data. For example, if a five second sample time is used with the sampling frequency of 25600 Hz, it sums up to 128000 measurement values which can be described with a single norm value. This method was used by Koistinen & Juuso (2015) where the biggest value out of five was chosen by using a sliding window, meaning there was one value for every 64000 measurement values (12800 Hz sampling frequency).

If the studied fault is known to cause impacts, the derivating of the measurement signal can increase the sensitivity of the fault detection (Lahdelma & Juuso, 2011a). The traditional way is to use displacement $x^{(0)}$, velocity $x^{(1)}$, and acceleration $x^{(2)}$ signals. Higher order derivatives $x^{(3)}$ and $x^{(4)}$ are useful for detecting the vibrations caused by fast impacts. They have been used in cavitation detection in Kaplan water turbine (Lahdelma & Juuso, 2008a). Analogue differentiators/ integrators can be used for real time calculations (Lahdelma, 1992; 1995; Juuso & Lahdelma, 2006). The generalised norms provide efficient solutions in various applications ranging from slow to very fast rotation (Lahdelma & Juuso, 2011b).

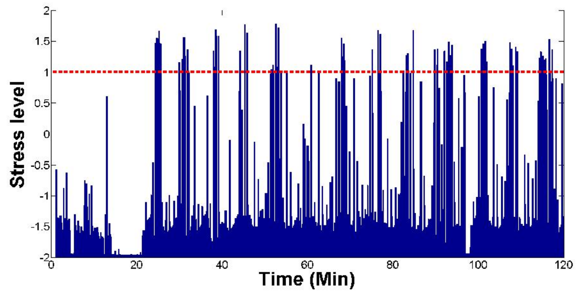

Fig. 2. Stress indexes of LHD dumper measured from working time of 120 minutes calculated with the norm with p=100. The dotted line indicates threshold value for higher stress levels.

Norms can be used in constructing of intelligent indices (Fig. 2). These indices can be used for the monitoring of the operational state or the condition of the machinery. Calculated norm values are scaled to a linguistic range [-2, 2] for the easy comprehension of events. These scaled values are understandable and can be used as regular process measurements. (Juuso, 2011)

2.1 Norms in axle monitoring

The first use case in this paper is about the stress and condition monitoring of the load haul dumper (LHD) front axle. The LHD had a clear target for condition based maintenance (CBM) since maintenance costs can form most of its operating costs. Reliability is very important and early decision making can bring savings due to decreased down time and avoided unplanned stopping which can break other parts in the process. (Laukka et al., 2015)

Calculated norms can be used for describing the development of condition when vibrations are measured from similar operating states and conditions. Vibration data used for this can be few seconds in length provided it is recorded from comparable operating states. Nissilä et al. (2014) used two hour daily vibration data recorded for 271 days in condition monitoring of the underground LHD. They formed surface indicating optimal values for the derivative and the order of the norm in the fault detection of this case.

These same norms can be used for the monitoring of stress and operating state in addition to condition. The stress monitoring requires the measurement data from the whole machine operating time in order to be used in the generating of the cumulative stress index (Fig. 3) for predicting the point where the break down occurs. The stress index also indicates the harmful stress spikes which in time form micro fractures and causes fatigue. This information can be used for operational monitoring and be sent to the machine operator in order to prolong the usable life of wear parts. (Koistinen & Juuso, 2015)

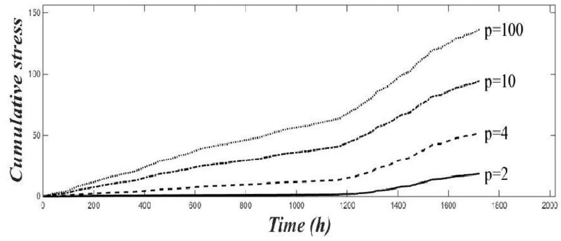

Fig. 3. Cumulative stress in a LHD front axle. Stress is inspected by norms with orders 2, 4, 10 and 100, respectively.

Stress indices are scaled according to the current condition of monitored part. Scaling function needs to be updated after fatigue causes changes in condition and the old range is no longer valid. Scaling is done by including the new values in calculations and the order of the norms can be re-evaluated if the distribution chances considerably. (Juuso 2011b)

2.2 Norms in grinding mill monitoring

Vibration measurements from a rod mill vibration are useful for inspecting the operating state or could be used for monitoring the performance and condition of steel rods. The grinding should be optimised for its large energy consumption. Grinding mills can have an average energy consumption of 11.6 kWh/t, while crushing can have more moderate 2.2 kWh/t (Wills, 2006). Local calculations could bring significant savings if they were used in the process control. Optimising the process would lower the energy consumption and only small improvements can make large savings.

Norm calculations have been used in the processing of the vibration data collected from the rod mill by Laurila et al. (2015). Four accelerometers were placed on the trunnion bearing bodies: two at the feed end and other two at the discharge end. Vibration monitoring in this case can be used for operational monitoring of mill fill level which is connected to the grinding performance and grinding mill energy consumption. Gugel & Moon (2007) achieved a 6.2% drop in the energy consumption of the grinding mill when vibration data from bearing housing was used in process control instead of mill power consumption reading.

In the stopping of a rod mill (Fig. 4), the rotation speed of the mill is reduced to 5 rpm (drop in blue line), the water feed is almost doubled for draining the mill. For the order p=2, the highest norm value was 1.8 m/s^2 (state 2) and the level with ore feed still active (state 1) the value was 0.6 m/s^2. State 3 describes the mill stoppage. The ascending norm values indicate that impacts grow stronger because of increased rod to rod collisions and rod to lining collisions. This case needs some further analyses and experimenting with sensor positioning before suitable algorithm can be implemented for on-site calculations. (Laurila et al. 2015)

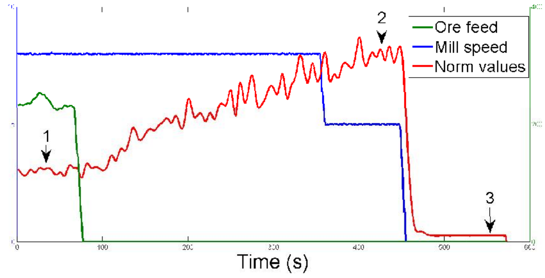

Fig. 4. The values of the norm (p=2) during the rod mill stopping (Laurila et al., 2015).

3. LOCAL CALCULATION

In (Rao, 1996) it was written about future developments that *"Coupled with radio technology, this brings forward the prospect of being able to stand next to a machine on a plant, and to find out, using small box (a PC) which you are carrying with you, almost anything that you need to know; a machine's current condition, its history, and how it is performing as part of the process right at that very moment."*. This is the idea that can be made possible with localised signal processing when managing large amounts of data. Information could be accessed straight from the on-site computer or by acquiring the machine id by scanning e.g. radio-frequency identification (RFID) tag and downloading data from the automation system database.

A worker can also use the measured and processed data for inspecting the operating state of the machinery. This can be helpful e.g. if there is some problem with the product and the cause is unclear. Monitoring of the operating state would also bring savings through a lower energy consumption and more uniform product. The linguistic range [-2, 2] can aid in machine inspection by presenting the machine condition or operating state with linguistic labels {*very low, low, normal, high, very high*} (Juuso, 2004). This way the person inspecting machinery does not necessarily have to have deeper understanding about the measurement values connected to machine operation or condition to see the state of the machine.

Continuous condition monitoring reveals changes in condition and can be used in predicting the development of the found fault. Previous measurements are needed in order to find out the amount of stress the part can withstand. When change in condition is revealed in advance, it enables the planning of maintenance strategy. One can continue to run the machine with the current operating level until a failure becomes too likely or the operating level can be lowered so that the operation can be continued until the next convenient point for the maintenance procedures. (Juuso 2015)

Local calculations can be easily tested by using commercially available programmable automation controllers (PACs). These devices can be used for data collection purposes like in cases presented in sections 2.1 and 2.2 and they are capable in the performing of signal processing calculations. The PAC used in presented cases was National Instruments CompactRIO 9024 with NI 9234 analog input module for vibration measurements. NI cRIO-9024 is a fitting base for algorithm development and testing for its modular hardware structure and easily updateable software. NI cRIO-9114 chassis was used for input modules. This chassis has a Xilinx Virtex-5 reconfigurable FPGA core to aid processing. The data acquisition code for FPGA and real-time unit was developed with the graphical coding environment of National Instruments LabVIEW software.

The faults in rotating machinery can be identified in most cases through amplitude and phase spectra. The presence of strong noise signals interferes with the measurement signal and leads to a faulty diagnosis. The FPGA based pre-processing can aid in high frequency acceleration data analysis by filtering the noise from the signal in real-time. (Shome et al., 2012) Several faults only appear in higher frequencies and according to Nyquist–Shannon theorem the sampling frequency has to be greater than twice the frequency of the highest studied phenomenon. If data needs to be recorded with very high sampling frequency beyond the processing power of CPU and bus bandwidth from several channels, the FPGA can aid in data acquisition and real-time processing (Zheng et al., 2014). Addition to LabVIEW software, MATLAB and its Simulink tool can be used in creating code for the FPGA. Development software provides simulation environment for testing the algorithm in order to validate the results. After testing and validation, the algorithm is converted into a hardware description language (VHDL) and implemented on FPGA. MATLAB DSP builder toolbox which uses Simulink environment for FPGA programming enables the algorithm design, system simulation, and translating of the code into VHDL. (Kashiwagi et al., 2014)

3.1 Wireless operation

Transferring the whole measured data wirelessly for processing can be difficult and unnecessary. It would require wide bandwidth and lots of energy. (Juuso, 2011) When the local feature extraction is not the option and the raw data needs to be transmitted to the maintenance center wirelessly for processing, one can consider available signal compression methods. In such case, the compressed data must be reconstructible to its temporal waveform. Guo & Tse (2013) listed several references to available compression methods for vibration data. One way is to extract relevant impulses from the acceleration data and then compress it in size before transmitting it forward.

In challenging location like a mining complex or other industrial location with dirt and interferences, several restrictions which need to be taken into account in building of a wireless network. Different technologies have their specific advantages and restrictions one needs to be aware of when choosing the right method. Industrial locations have special requirements for wireless networks. The network must be reliable, cover the range needed, have wide enough bandwidth, work in spite of noise, have security issues covered, and be fault-tolerant just to name a few requirements. On the other hand wireless communication enables the mobile data inspection and control of components not reachable with wires. (Egea-Lopez et al., 2005)

Underground location presents difficulties for wireless operation such as unreliable and unpredictable wireless links. Multipath fading is caused by reflection, diffraction, and refraction. Wireless network performance can be adjusted by means of modelling. In future, network nodes can contain physical information about their environment for estimating optimal transmission power for more reliable operation and network life time. (Farjow et al., 2015)

Some data about the machinery may be needed when inspecting operation in the field. A persons needing the status information or data considering a certain machine requires some way to access this information and some assurance that the data comes from the machine in question. This may be achieved through the usage of active or passive RFID tags and suitable reader. The passive RFID tags are much cheaper and more reliable than active battery powered tags. Passive tag is powered inductively by an antenna, allowing it to transmit its information back to the reader. These passive tags have limited communication range which is limited by the output power of the antenna. Modern passive tags can have the maximum range of 5 – 10 meters which is enough for maintenance checks. Advanced active tag can also contain logic, memory, and a microprocessor to enable writing and algorithms for encryption and security. Simple tag contains only the ID number which can be used for identifying a certain machinery or sensor from the information database. (Lehpamer, 2008)

Historian data may need to be stored for some later analyses or inspection. This can be difficult if recorded data is of high frequency and from several sensors. A wireless link would need lots of bandwidth and high reliability of the signal to be usable and storing this amount of data would be expensive. Data compression can aid in saving and sending this more detailed data. The use of data needs to be evaluated carefully before choosing the compression algorithm. The data compression here can mean both lossless methods and methods from which the original signal cannot be recovered. (Thornhill et al., 2003) Vibration nodes can be utilised into using divide-and-compress compression scheme. Huang et al. (2015) presented a lossless compression scheme for bearing vibration data in wireless sensor networks which achieved the average compression ratio of 59.01%.

3.2 Wireless sensors

Locations that are hard to reach or have other restrictions for wired sensors like rotation, can be monitored with wireless sensors. Wireless sensors have certain restrictions in vibration monitoring such as low sampling frequency and a limited battery lifetime. Low cost sensors can have computational capabilities built in for local calculations. Karuppiah et al. (2014) studied the power consumption of a vibration node network when the signal was processed in nodes before transmitting. Sophisticated sensor nodes can have embedded microprocessors for simple signal processing operations such as filtering or pattern recognition. More complex algorithms would require a faster processor and more memory and power. Merendino et al., (2011) implemented the methods based on

Fourier transform and wavelets in low cost sensor node. (Karuppiah et al., 2014)

In addition to the low sampling frequency of many node systems, the wireless sensor networks (WSNs) can have synchronization problems at higher sampling frequencies. This synchronization problem can be improved with dual processor construction. Modern wireless nodes are capable up to 20 kHz sampling frequency but the wired system has higher resolution (Huang et al., 2015)

4. DISCUSSION

Local calculations efficiently focus on knowing of the current machine condition and bring out new information about the machine operation. Knowledge-based maintenance or maintenance done based on previous experience can work with machinery when wear part is under constant, not varying, stress and part to be replaced is of uniform quality. Normally, the case is that the stress varies and there can be variations between the uniformity of replacement parts as well. Real-time monitoring detects upcoming failures well ahead and opens possibilities for formulating the maintenance plan with minimised down time. Monitored part has a certain stress resistance and when it is taken into account, the machine operation can be controlled in such way that the operating time can be prolonged until next scheduled stoppage or other suitable point.

If the process is such that the vibration data will be used for further analysis and research, the raw vibration data or at least some interesting parts of it should be saved. The continuous data collection of unprocessed data would be expensive and the analysis of long periods with complex algorithms would take huge amount of time. This could be avoided with triggering. One defines triggering for the interesting event in process and data is recorded for the predefined length or end can be determined by another trigger. This solution could enable the analysis of raw data from exceptional or unwanted situations without requiring enormous amounts of hard drive capacity. This amount of raw data could also be transferred to the automation system wirelessly when it comes from a sparsely occurring event.

The use of norms requires the linking of values into physical events occurring in the monitored target. After these values are connected into real-life events, the calculations can be implemented into the localised calculation point from which they can be acquired or automatically transferred into the specific database. In addition to the local maintenance, this information about the condition can be utilised by the spare part supplier so that it can prepare to deliver replacement part in advance. The operation and condition of similar parts in known operating point can be compared if this information is shared by the machinery users. This would provide valuable information for the development process of the parts manufacturer.

In the case of remote controlled mining equipment such as the LHD, the norms are used in the monitoring of stress. Since the operator cannot feel or otherwise sense stronger vibrations, indicating greater stress and the visual indication of stress levels can guide in more cautious operation. Stress indices can be marked with traffic light colors since this indication gives a better representation of events than some number that can be ignored more easily. The scaling of indices can be updated according to needs of changed conditions or states. Changes in operation or condition may sometimes require adjustments in vibration calculations. Calculation of norms can be easily adjusted by changing the order of the norm or possibly by selecting a different order of derivation.

5. CONCLUSION AND FUTURE STUDIES

On-site norm calculations can be used in varying vibration monitoring purposes. Every case needs preliminary analyses for solving the connections between the norm values and physical events. Future studies include the implementing of optimised algorithms in presented cases.

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