Lean Instrumentation Framework for Sensor Pruning and Optimization in Condition Monitoring

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Abstract

This paper discusses a lean instrumentation framework for guiding the introduction of the lean concept in condition monitoring in order to enhance the organizational capability (i.e. human, technical and management trichotomy) and reduce the complexity in the maintenance management systems of industrial companies. Additionally, decision-making, based on severity diagnosis and prognosis in condition monitoring, is a complex maintenance function which is based on large data-set of sensors measurements. Yet, the entirety of such decision-making is not dependent on only the sensors measurements, but also on other important indices, such as the human factors, organizational aspects and knowledge management. This is because, the ability to identify significant features from large amount of measured data is a major challenge for automated defect diagnosis, a situation that necessitate the need to identify signal transformations and features in new domains. The need for the lean instrumentation framework is justified by the desire to have a modern condition monitoring system with the capability of pruning to the optimal level the number of sensors required for efficient and effective serviceability of the maintenance process. It is concluded that there are methodologies that can be developed to enable more efficient condition monitoring systems, with benefits for many processes along the value chain.

1. Introduction

Today's competitive business climate has given rise to the need for faster time-to-market, lower costs and increased initial product quality. In the process industry, increased automation has made the competitive business climate even tougher (Abrahamsson & Johansson, 2009). In most industrial companies, increased automation in the process chain could also imply increased complexity of carrying out some key decision-making tasks, such as condition monitoring, as a result of the increased level of instrumentation involved. Decision-making (i.e. severity diagnosis and prognosis) in condition monitoring is a complex maintenance function which is based on hundreds of sensors measurements. Yet, the entirety of such decision-making is not dependent on only the sensors measurements, but also on other important indices, such as the human factors, organizational aspects and knowledge management. Unreliable decisions can emanate from the diagnosis of machinery whose failure modes are hidden, and thus do not show a visible pathology to the human operator. The consequence of such unreliable decisions is the increase in maintenance and operational costs derived from the costs of human/labour intervention, replacement of failed parts, and lost production. This issue therefore, brings to the fore the challenge of reducing or eliminating the complexity associated with condition monitoring and at the same time increasing its coast-effectiveness as well as the reliability maintenance decisions emanating from the system.

In attempts to address this issue, non-destructive methods (e.g. the analysis of vibration in rotating machinery) have been used to diagnose machinery with such failure non-detectability consequences. Yet, the use of these methods entailed the adaption of new, but very expensive technological instruments which increase the cost of maintaining the production system. Such increase in maintenance cost against the backdrop of increased industrial competition signifies a productive challenge that confronts most firms. In order to overcome this challenge, firms need to be provided with a cost-effective and less complex condition monitoring design approach that consists of the requisite level of instrumentation to facilitate efficient and effective serviceability of the process value chain.

Thus, the purpose of this paper is to introduce a new approach to lean instrumentation which allows for the embedment of lean capabilities inside the process value chain by reducing the complexity and enhancing the cost-effectiveness of maintaining and managing the process value chain of industrial companies. The objective is to develop a lean instrumentation framework for sensor pruning and optimization in condition monitoring of production systems. The question that necessitated the purpose is as follows. Can a combination of Lean-Thinking Philosophy (LTP) and Bio-Inspired Principles (BIP) be used as a conceptual base to develop a framework for pruning and optimizing the level of instrumentation in the production value chain? In other words, can a combination of LTP and BIP be used as a conceptual base to develop a framework for the pruning and optimization of the number of vibration-detecting sensors to be installed on industrial electric motors? This paper presents a conceptual framework that linking LTP and BIP that could be used to guide the pruning and optimization of the number of vibration-detecting sensors.

2. Traditional approach in condition monitoring

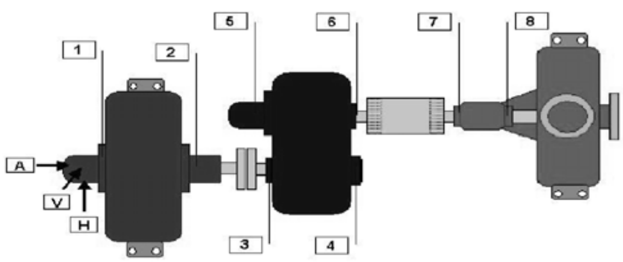
Any manufacturing unit process can be regarded as a conversion process of material, energy, and information. The process should be monitored carefully to produce an output that can meet the requirements. When the process is operated by humans, it is monitored with sense organs such as vision, hearing, smell, touch, and taste. Sometimes, information obtained through multiple sense organs is used to guide decision making, and the brain plays an important role in processing such information. In general, humans are very capable as process monitors because of the high degree of development of their sensory abilities, essentially noise-free data (unique memory triggers), parallel processing of information, and the knowledge acquired through training and experience. Limitations are seen when one of the basic human sensor specifications is violated; something happening too fast to see or out of range of hearing or visual sensitivity owing to frequency content. These limitations have always served as some of the justification for the use of sensors. The sensor system is generally composed of sensing, transformation/conversion, signal processing, and decision-making. The output of the sensor system is either given to the operator via a human-machine interface or directly utilized to control the machine. Objectives, requirements, demands, boundary conditions, signal processing, communication techniques, and the human-machine interface of the sensor system have to be described.

2.1. Vibration analysis

Traditionally, machine operators have used auditory techniques to detect specific problems in rotating machines. Typical problems (e.g., due to wear or insufficient lubrication) cause excessive vibration of the machine or some of its parts. This vibration can often be perceived by a trained operator if the background noise is not too high, but the subjective nature of the approach makes it inaccurate and inefficient in determining if the overall situation is acceptable or not. In particular, it is difficult to reliably estimate the remaining useful life via manual inspection, which is a key variable for optimal maintenance, production and business decisions. Nowadays, systematic approaches are therefore used to measure vibrations, and to detect and identify problems in machine components.

2.2. Number and position of measurement devices

The International Standard organization has provided a standard (ISO 10816-1/6) for the evaluation of machine vibration by measurements on non-rotating parts. The standard guides in locating and measuring specific points of vibration in the horizontal, vertical and axial planes, and thus makes data analysis easier. The orientation of each point of measurement is an important consideration in configuring the database for analysis. There is an optimal orientation for each measurement point of the machine in a predictive maintenance program. The measurement points should be numbered sequentially starting with the main drive. Any numbering convention may be used, but this must be consistent in order to allow for the immediate identification of point locations during the analysis and diagnosis. The cluster of points per axis must also allow the analyst a clear view of the problems in each component. In the case of electric motors, two points of measurement corresponding to the housing of the bearings are required. At each point, it is normal to take two measurements, in a horizontally and vertically, reflecting different pathologies vibration obtained in two different directions, despite being the same pocket. This allows the analyst a clear view of the problems in each component. In the case of a more complex machine that is coupled to fan motors or pumps, but having a single speed, it would act similarly. Some configurations have more points of measurement. A case in point is driver (motor or turbine) with a gearbox and pump. In this configuration, eight bearings, with their pockets can be found, as it is shown in figure 1 below for a turbine coupled to a gearbox and a pump. In this case, the following points are measured;



- Turbine: 1A, 1H, 1V, 2H, 2V.
- Gearbox: 3H, 3V, 4ª, 4H, 4V, 5ª, 5H, 5V, 6H, 6V.
- Pump: 7A, 7H, 7V, 8H, 8V.

1	Turbine Non Coupling Side	5	Gearbox Low Speed Non Coupling Side
2	Turbine Coupling Side	6	Gearbox Low Speed Coupling Side
3	Gearbox High Speed Coupling Side	7	Pump Coupling Side
4	Gearbox High Speed Non Coupling Side	8	Pump Non Coupling Side

Figure 1. Details of the measuring points on a machine train: turbine-gear-pump

For this machinery, 20 measures of vibration velocity are obtained at different points, which give an idea of the complexity of measurement process in such machines. A serious problem in developing a vibration-based damage detection method is that a large number of sensors are needed to locate damage on large structures (Doebling, 1996; Friswell, 1997). Unfortunately, vibration monitoring has become a labour intensive and time consuming job which made it impractical for large scale use without increasing enormously the complexity of the manufacturing system and resources devoted.

3. Introducing the lean thinking

The core philosophy of lean thinking is to maximize productive value through the minimization of wastes in the process chain. Thus the introduction of the lean concept (Womack and Jones, 1996) in the condition monitoring component of a firm's maintenance system will require the analysis and optimization of the value, value stream, flow, pull, and perfection of the firm's system in order to remove non-value added activity, or waste. The issue of value in maintenance is a complex one requiring several different value strategies to be combined within one system. Humphreys (2008) has noted that complexity drives entropy which absorbs resources and energy from surrounding sources. These sources could be related to waste which forms an interrelationship with a complex system. In a firm, technicians might have a definition of value which may differ from those of their managers. According to Green (1994), this is a problem at the heart of value management issues. In contrast, Garnett, Jones, and Murray, (1998) noted that several key differences of value management could become immediately apparent when the principle of lean thinking is applied to the condition monitoring task in the maintenance system with a focus on meeting customer needs. Focusing on customer will also require that the condition monitoring task in the maintenance system also adopt a product focus, in order to enable a long-term dialogue between the nature of value and how the product delivers it. The value stream identifies all those steps required to make a product. The key technique behind the value stream is that of process mapping (Garnett, et al., 1998). However, it is process mapping for understanding how value is built in to the building product from the point of view of the client. At a strategic level it offers a perspective on defining what is to be done.

The traditional condition monitoring process pushes the technician into an often protracted development process where risk and uncertainty are prevalent. The principle of flow suggests a vision where the ability to define quickly what the technician measures and interprets in condition monitoring and subsequently customising a well understood process to best fit those process means that severity measurements in condition monitoring can be carried out more predictably when required. This is a key concept at the strategic level because it defines the need for a way of working and organising condition monitoring task that could make it to become a way of life with an inherent culture. To achieve perfection means constantly considering what is being done and how it is being done and harnessing the expertise and knowledge of all those involved in the processes to improve and change it (Garnett, et al., 1998). The traditional condition monitoring process is ineffective in developing products, choosing the key components for the maintenance system, coordinating the instrumentation design and managing the supply chain. This leads to an inefficient and time consuming process of design coordination once key contracts have been let and a poor engineering fit on site.

The traditional condition monitoring process assumes that technician make can make good subjective decisions from their comparison of the point to point vibration measurements to the ISO standards measures. Consequently there are no arrangements within the structure for learning, innovation or the development of skilled people needed to deliver quality and efficiency in the process. The starting point for the lean instrumentation process in condition monitoring is the premise that fewer sensors usage will result in an efficient and effective system design that allows for simultaneous data measuring and interpretation. Over time, these products (i.e. maintenance system) become increasingly customer focused, more cost effective and have an ability to be delivered very quickly. This develops a culture, which can define value because it understands both the customer and the product in great detail (Garnett, et al., 1998). This will lead the company to redefine its maintenance system through the application of the lean thinking principles at a strategic level.

3.1. Lean sensor

Lean sensor is a form of lean approach that can be used to design the optimization of the number of vibration-detecting sensors to be installed on industrial electric motors. This will enhance knowledge creation in the shift from the complexity of the traditional condition monitoring approach to a lean one. Truchard (2004) noted that virtual instrumentation (i.e. using customizable software and modular measurement hardware to create user-defined measurement systems) can be used to optimize the product design and development process by delivering an overall leaner and more streamlined method to link test and design. That is, it can be used to overcome the challenges of introducing lean sensors in the maintenance process of condition monitoring by using a flexible test platform that adapts to new technologies and facilitates the integration of real-world data into all stages of the design flow. Truchard (2004) explained that virtual instrumentation solidifies the relationship between lean design (i.e. using test data to improve simulation models) and lean test (i.e. using simulation results to refine tests) by facilitating the use of real-world data to improve the quality and accuracy of design iterations and simulations. In condition monitoring process, the diagnosis component is reflected by the lean design aspect of the virtual instrumentation, while the prognosis component is reflected by the lean test aspect of the virtual instrumentation. According to Truchard (2004), virtual instrumentation pulls together diverse system components to create an open test platform that takes advantage of the latest technologies, and with advances in virtual instrumentation software, the complexities of test technologies, such as condition monitoring, could be minimized so that maintenance engineers can focus on developing a better systems.

3.2. Bio-inspired principles

Biologically-inspired computing is an active and innovative area of research and scientific discipline. The overall goal is to observe and understand the functional processes in living organisms, and which understanding are then translated into computing methods for solving complex problems in engineering as well as in other scientific disciplines. By relying on well-established biological and social paradigms, large quantities of small processing units, particularly sensors and actuators, that show capabilities of self-management are designed and implemented in engineering systems. This meant that complex system behaviour at the macroscopic level can be mapped in a non-linear fashion derived from the heterogeneous interactions at the microscopic level. Biologically-inspired approaches that are used in this wise include; artificial neural networks, reservoir computing, evolutionary algorithms, cellular automata, amorphous computing, and computer immune systems, among others. Arguing from the perspective of virtual instrumentation, bio-inspired lean thinking in condition monitoring (CM) could be conceived by solidifying the relationship between a “lean CM design” that need to be firstly developed by using test data to improve simulation models, and a “lean CM test” whose development could be bio-inspired through the use of a biological process to simulate results that could be used to refine tests. As Truchard (2004) noted, this bio-inspired lean CM test approach could facilitate the use of real-world data to improve the quality and accuracy of CM design iterations and simulations.

4. Conceptual framework for lean instrumentation

Based on the reviewed literature, the bio-inspired lean instrumentation process for sensor installation can be conceived to entail four stages as highlighted in figure 2 below. The first stage is to generate sensor data using the usual traditional measurement. The second stage is to use the decision derived from stage 1 to generate knowledge by carrying out a diagnosis of the sensor data (lean design) and then a prognosis (lean test). The third stage is to carry out sensitivity analysis for sensor pruning using a bio-inspired medium. This test helps in determining whether an installed sensor could be classified as redundant or otherwise, based on the level of its measured sensitivity. The fourth stage is to introduce tools for decision-making in space to enhance sensor removal. In this stage redundant sensors can be removed, and maintenance people can rely on measures from the remaining sensors to make accurate decision.

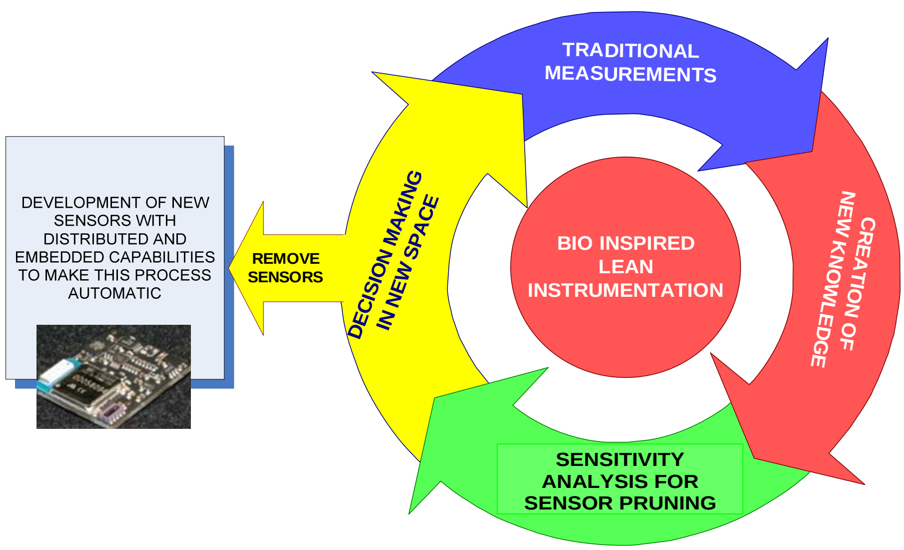


Figure 2. Framework for lean instrumentation process

The framework shown in figure 2 above has the potential of assisting in finding out the right domains where instrumentation redundancies could be easily identified. The identification of the redundant sensors could be used as platform to develop new sensors with distributed and embedded capabilities that could result in an autonomous decision-making process. The evolution of such autonomous decision-making process will therefore eliminate the complexity entailed in the work organization of traditional processes for which decision-making requires a significant amount of sensor-output measuring time and strenuous human effort. In other words, the autonomous decision-making process is reflective of lean, due to its introduction of economy in human effort and also efficiency in the work organization. In the case of condition monitoring (CM), the block diagram shown in figure 3 below could be used to guide the application of the lean instrumentation framework (figure 2 above) to reduce the complexity of the CM measurement process towards improving both the technical and human activities, as well as enhancing the firm's productive capacity and customers' satisfaction to service delivery.

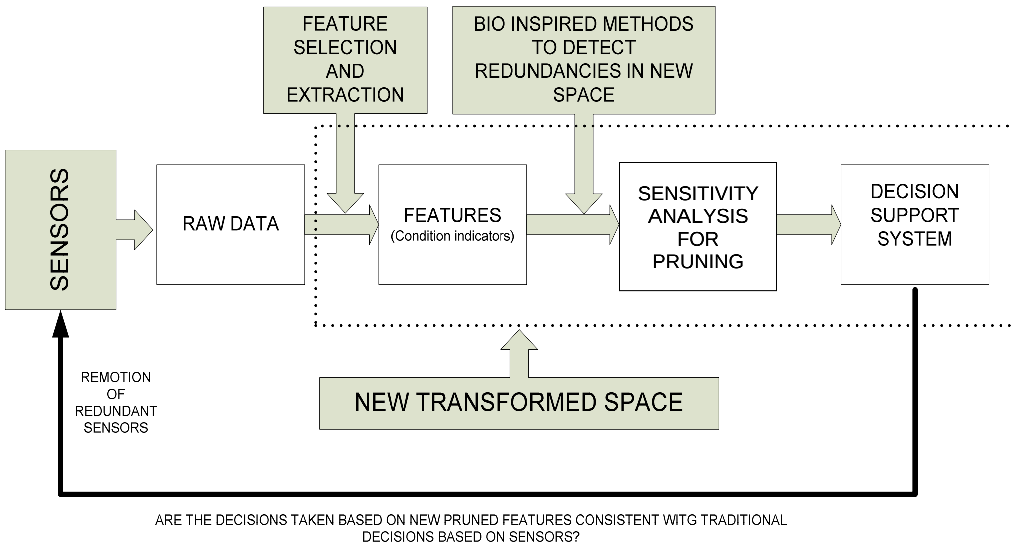


Figure 3: Block diagram for applying the lean instrumentation (sensors) framework in condition monitoring

For this purpose some signal transformations and features in new domain have to be found. Identifying significant features from large amount of measured vibration data is one of the major challenges for bearing defect detection, diagnosis and automated defect diagnosis. Feature extraction helps to maximize the useful information from the raw data. Identifying relevant features leads to accurate, faster and easy defect diagnosis. Selected features should be sensitive to machine faults. They should also be robust to background noise. Another important consideration in feature selection is that computation requirement for extracting features from condition monitoring data should be less. Features are extracted from raw vibration data using various signal processing methods such as time domain, frequency domain and time-frequency analysis. Feature extraction consists of feature construction and feature selection.

5. Sensor pruning in condition monitoring: A case study

This case study was conducted within the proposed framework (see figure 2 above) to find out the right sensor domains where redundancies are easily identifiable and which could be used as a platform for the introduction of lean instrumentation in the production system. This is because the traditional approach of point by point comparison denies the possibility of disagreement between vibrations in different locations that could arise due to machine age or installation problems. The consequence of this is that it can lead to false alarms and unnecessary interventions, and by implication increases maintenance cost.

5.1. Methods and materials

3.1.1 Data Collection

Guided by the proposed framework for bio-inspired lean instrumentation process (figure 2), and the block diagram for applying the lean instrumentation framework (figure 3), the following three stages were used to guide data collection. In the first step, data generated using the traditional measurement approach. In the traditional conditioning monitoring approach (i.e. step 1), vibrations are measured by trained individuals at several points along the machinery, as highlighted in figure 4 below.

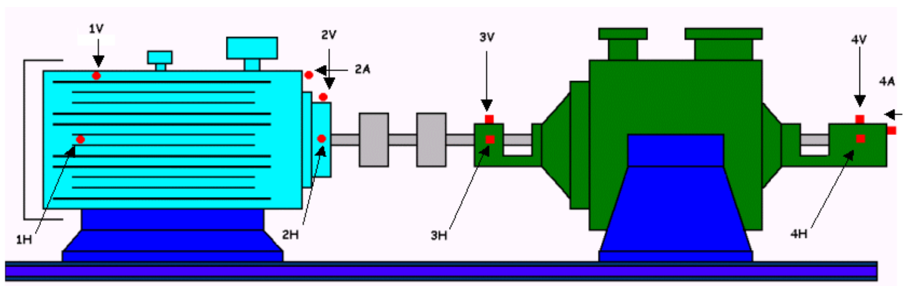


Figure 4: Layout of centrifugal pump showing point to point measurement nodes

Afterwards, the individual compares these point to point measurements to the reference values in the standard chart in order to be able to identify points with significant severity of vibration, and then take appropriate maintenance decisions. In the second step, the data generated in the first step was used to create knowledge by carrying out a diagnosis of the data (lean design) and then a prognosis (lean test). In the knowledge creation through lean instrumentation (i.e. step 2), the diagnosis of the test data from the traditional measurements (step 1) is used to introduce a lean sensor architecture design that can be used to simulate and improve installed sensors. A prognosis (i.e. lean test) is then carried out by using the simulation results to refine tests by facilitating the use of real-world data to improve the quality and accuracy of design iterations and simulations. In the third step, the knowledge generated in the second step is fed into a bio-inspired medium (artificial neural network) to carry out sensitivity analysis for pruning the traditionally installed sensors. In this step, new features extracted from the traditional installed sensors are pruned in order to eliminate redundant channels which contribute irrelevant information.

3.1.2 Data Analysis

Identifying significant features from large amount of measured vibration data is one of the major challenges for bearing defect detection, diagnosis and automated defect diagnosis. Feature extraction helps to maximize the useful information from the raw data creating new information embedded into these data which could otherwise remain useless. Identifying relevant features leads to accurate, faster and easy defect diagnosis. Selected features should be sensitive to machine faults. They should also be robust to background noise. Another important consideration in feature selection is that computation requirement for extracting features from condition monitoring data should be less. Features are extracted from raw vibration data using various signal processing methods such as time domain, frequency domain and time-frequency analysis. Feature extraction consists of feature construction and feature selection. The time domain method has been used to analyze the vibration signal in the condition monitoring of the rolling element bearings, creating new features based on current raw data (Shiroishi, 1997; Azovtsev, 1996). In the traditional time domain technique, shock pulse values and values of the statistical parameters such as peak value (Pv), root mean square value (RMS), kurtosis value (Kv) of the signal which are used to monitor the condition of the bearing were extracted. Non-dimensional statistical parameters such as crest-factor (Crf), clearance factor (Clf), impulse factor (Imf) and shape factor (Shf) were also extracted. Weibull negative log-likelihood value (Wnl) and normal negative log-likelihood value (Nnl) were also extracted. The extraction of each respective parameter is achieved by applying the appropriate equation as highlighted below.

$$\text{Peak value, } Pv = \frac{1}{2}\left(\max[x_i] - \min[x_i]\right)$$

$$\text{RMS value} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[x_i]^2}$$

$$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[x_i - \bar{x}\right]^2}$$

$$\text{Kurtosis value, } Kv = \frac{\frac{1}{N}\sum_{i=1}^{N}\left[x_i - \bar{x}\right]^4}{(RMS\_value)^4}$$

$$\text{Crest factor} = \frac{Peak\_value}{RMS\_value}$$

$$\text{Clearance factor} = \frac{Peak\_value}{\left(\sqrt{\frac{1}{N}\sum_{i=1}^{N}|x_i|}\right)^2}$$

$$\text{Impulse factor} = \frac{\text{Peak\_value}}{\frac{1}{N}\sum_{i=1}^{N}|x_i|}$$

$$\text{Shape factor} = \frac{RMS\_value}{\frac{1}{N}\sum_{i=1}^{N}|x_i|}$$

If $f(x_i;\theta_1,\theta_2)$ is the probability density function (pdf), negative likelihood function can be computed as:

$$-\Lambda = -\sum_{i=1}^{N}\log\left[f(x_i;\theta_1,\theta_2)\right]$$

Wnl and Nnl can be computed by substituting Weibull pdf and normal pdf in previous equation.

In the sensitivity analysis for sensor pruning, irrelevant input features were identified and removed, which reduced the size of the network, the complexity and the training time. Sensitivity based pruning method is used to evaluate the effect of removing an input variable from the fully connected network. With this algorithm, candidate architectures are constructed by evaluating the effect of removing an input variable from the fully connected network. These are ranked in order of increasing training error. Inputs are then removed following a “Best First” strategy (i.e. selecting the input that, when removed, increases the training error least).

4. Results

Vibration signal parameters calculated for each point in the machine layout (figure 2) using raw data in time domain obtained from the traditional measurement created new knowledge in the form of transformed vibration signals in a new space and time domain. The extracted parameters that constituted the new coordinate space in the new transformed domain are the peak values (Pv), root mean square values (RMS), kurtosis values (Kv), crest factors (Crf), (v) clearance factors (Clf), (vi) impulse factors (Imf), shape factor (Shf), Weibull negative log-likelihood values (Wnl), and the normal negative log-likelihood value (Nnl). The results obtained from the defect diagnosis performed with artificial neural network trained using all the 10 time domain input features (see figure 4 above) obtained from the signals for the different measurement points is shown in figure 5 below.

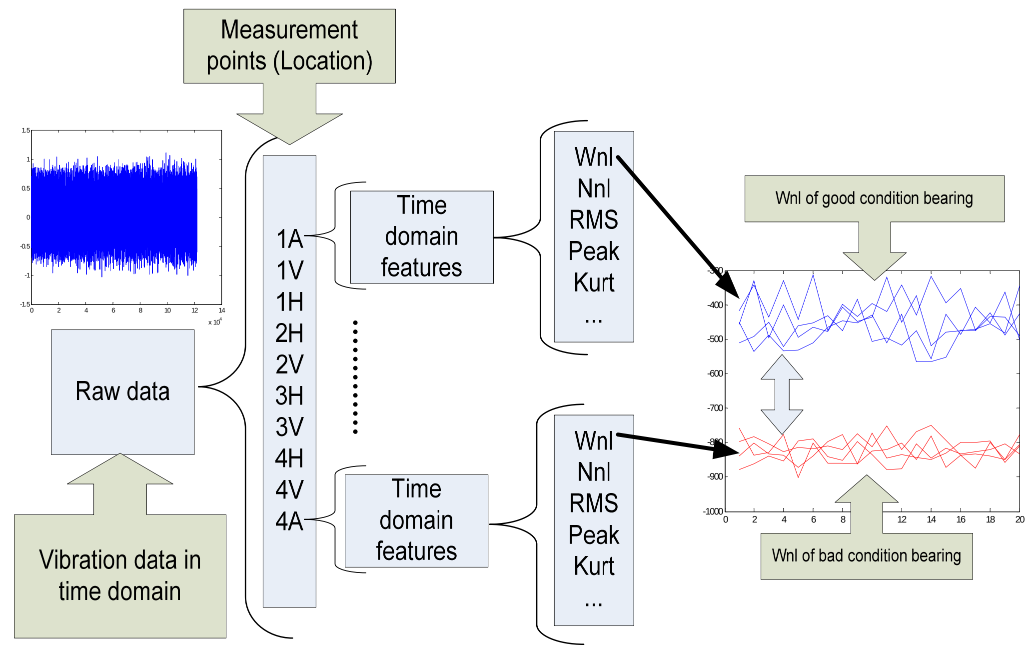


Figure 5: Defect diagnosis performed with artificial neural network showing trained input features obtained from signals for the different measurement points.

As it is shown in figure 5 above, and in relation to the lean instrumentation framework (see figure 2), selected features of vibration in time domain (new knowledge) from the signals for the different measurement points of 10 time domain input features were extracted. As it is observable from the different points, the generated features for the bearing diagnostics indicate sensor locations with redundant features, and which sensors do not impact on the measured vibrations for determining the condition state of bearings (i.e. either in good or bad conditions). These sensors with redundant features could therefore be pruned (i.e. removed) without any effect on the functionalities of the remaining sensors and the information to be generated in the transformed space.

5. Discussion

The result has shown that no sensing device is one hundred percent reliable and it is possible to identify redundancies in installed sensors which could be removed and by implication introduces a sense of lean in sensor installations which also reduces the complexity of associated with the traditional condition monitoring process. Reliable theoretical models relating sensor output and process characteristics are often difficult to develop because of the complexity and variability of the process and the problems associated with incorporating large numbers of variables in the model. The results highlight the possibility of identifying and isolating redundant sensors, and also the identification of the relevant sensors that need to be installed and their installation points on machines. Ability to identify these relevant sensors and their positions on the machines makes it easier for the condition monitoring task to be carried out by the human, as well as provide a leeway for introducing innovation in sensors with increased reliabilitities to further enhance the condition monitoring process.

A possible way to increase the reliability is to use virtual sensors (with performance capability of multiples of sensors) which will make the human-based monitoring system used in the traditional condition monitoring redundant. The fusion of variety of information is a very suitable means of obtaining a more comprehensive view of the state and performance of the process (Chiu et al., 1986). Sensor fusion is a powerful tool for making the monitoring system more flexible so that the various types of malfunctions that occur in the process can be detected. The virtual integration of similar types of sensors (i.e. a replicated sensor system) can contribute towards improving the reliability and robustness of the monitoring system. The virtual integration of different types of sensors (i.e. disparate sensors system) can also make the monitoring system more flexible by providing data for the decision-making process that has a low uncertainty. Virtual sensors could pull together diverse system components to create an open test platform that takes advantage of the latest technologies. By this, the complexities of test technologies, such as condition monitoring, could be minimized so that maintenance engineers can focus on developing a better systems. Therefore virtual sensors developed from the sensor pruning provides an avenue for reducing the complexity of integrating test equipment and interface technologies (as it is in condition monitoring) with software tools for design and simulation. Thus removal of the complexity associated with the traditional condition monitoring process would improve the work organization process with minimal decision-based work demand on the human operator whose functional development would be enhanced. By implication, the work system will entail an ability to define quickly what the human operator needs to measure and interpret in the condition monitoring process. This will signify a well understood work process whereby severity measurements in condition monitoring can be carried out more predictably when required. Thus the lean instrumentation framework can serve as an important tool for pruning the number sensors to be installed on production systems in order to allow a semblance of perfection in the production value chain and satisfaction to both the human operator and the client. This is because, the lean framework could help in the attainment of perfection in conditioning monitoring by it is character of guiding the pruning of sensors, and enabling the harness of expertise and knowledge of all those involved in the processes to improve and change it (Garnett, et al., 1998).

5. Conclusion

In this paper we describe the value of introducing the lean concept in condition monitoring and we outline a framework that serves as a starting point for further development of methodologies and demonstrators. We discuss the role of excessive complexity in the condition monitoring instrumentation and the maintenance management system, and we outline how the complexity can be reduced in order to increase the production and organizational capacity (e.g., human, technical and management trichotomy). The decision-making process in condition monitoring is a complex maintenance function that requires efficient methods for the analysis of sensor data. This decision process depends also on other variables, such as business constraints, production constraints, organizational aspects, and human aspects. We discuss the possibility to use bio-inspired computing techniques to deal with the complexity in these systems, because the cost of a traditional model-based approach can prevent development of decision support systems that include the key aspects. Such systems should also address the important aspect of knowledge management. We conclude that there are methodologies that can be developed to enable more efficient condition monitoring systems, with benefits for many processes along the value chain. Further work is needed to evolve this framework and to develop demonstrators using some of the techniques introduced here.

References

Abrahamsson, L., Johansson, B., Johansson, J., 2009. Future of metal mining: sixteen predictions. International Journal of Mineral Engineering, 1 (3), 304-312.

Azovtsev, A., Barkov, A., Carter, D. (1996). Improving accuracy of rolling element bearing condition assessment. In Proceedings of the 20th Annual Meeting of the Vibration Institute, pp. 27–30.

Doebling S.W., Farrar, C. R., Prime, M. B., Shevitz, D. W. (1996). Damage identification and health monitoring of structural and mechanical systems from changes in their vibration characteristics: A literature review. Los Alamos National Laboratory Report LA-13070-VA5.

Bassan, J., Srinivasan, V., Knights, P., Farrelly, C.T., 2008. A day in the life of a mine worker in 2025. In: Sayden, S. (Ed.), Proceedings of the First International Future Mining Conference and Exhibition, The Australian Institute of Mining and Metallurgy, Sydney, NSW, pp. 71 – 78.

Bennett, J. and Jayes, S. (1998). *The Seven Pillars of Partnering.* Thomas Telford, London.

Chiu, S., Morley, D. and Martin, J. (1986). Sensor data fusion on a parallel processor. *Robotics and Automation. Proceedings. 1986 IEEE International Conference on*. 3, 1629- 1633. doi: 10.1109/ROBOT.1986.1087441

Friswell, M.J., Penny, J. E. (1997). The practical limits of damage detection and location using vibration data. 11th Symposium on Structural Dynamics and Control, 12–14 May, Blacksburg, VA, USA.

Garnett, N., Jones, D. T., and Murray, S. (1998). Strategic Application of Lean Thinking. In: Proceedings IGLC ’98, Guaruja, Brazil.

Gray, C. (1996) *Value for Money; Helping the UK Afford the Buildings it Likes*. Reading Construction Forum, University of Reading, Reading.

Green, S.D. (1994). "Beyond Value Engineering: SMART Value Management for Building Projects.” *International Journal of Project Management*, 12 (1), 49-56.

Humphreys, P. (2008). How properties emerge. In: Bedau, M. A. & Paul Humphreys, P. (Eds.), *Emergence: contemporary readings in philosophy and science***.** The MIT Press: Cambridge, Massachusetts.

Latham, M. (1994). *Constructing the Team*. HMSO, London, U.K.

Shiroishi, J., Li, Y., Liang, S., Kurfess, T., Danyluk, S. (1997). Bearing condition diagnostics via vibration and acoustics emission measurements. Mechanical Systems and Signal Processing, 11, 693–705.

Truchard, J. (2004). Outlining the future of lean design with lean test. SAE 2004 World Congress, Detroit (Business Wire), March 10, 2004. Retrieved from: http://findarticles.com/p/articles/mi_m0EIN/is_2004_March_10/ai_114100491/?tag=content;col1

Womack, J. P. and Jones, D.T. (1996). *Lean Thinking: Banish Waste and Create Wealth in your Corporation*. Simon and Schuster, New York.