Architectures and Key Points for Implementation of E-maintenance Based on Intelligent Sensor Networks

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ABSTRACT

During the past few years industrial predictive maintenance has benefited from new developments in hardware and software systems. A key conclusion is that to maximize results, these systems need to be smarter with learning capabilities. Moreover, wireless sensor networks have led to a new revolution in the field of e-maintenance, offering new possibilities in measurement collection, aiming to empower monitoring with more advanced features. In what way can wireless sensor networks be applied to industrial maintenance? How can novelty detection be implemented on these systems? How can such systems scale up to offer distributed intelligence? This paper presents the WelCOM research program's approach on the aforementioned matters answering many questions that relate to intelligent sensor systems in the field of e-maintenance and proposing flexible architectures for the implementation of these systems.

1. INTRODUCTION

e-Maintenance empowers maintenance engineering and management with ICT tools that streamline the delivery of maintenance services, from the field level of measurements collection all the way up to maintenance decision support (Holmberg, 2010). It contributes to the aim of sustainable development in society and the proper function of a whole range of engineering assets, ranging from factories and, power plants to transport and built infrastructure. Well-established maintenance practices can lead to improve the efficiency of resources and production management, while supporting the quality and safety procedures and minimize environmental impact, thus contributing to the sustainability of the enterprise. Maintenance activities, such as repairs and service actions, only take place when actually needed, which is the essence of Condition-Based Maintenance (CBM). The development of low-cost and micro-size integrated sensors for taking machinery measurements, the upgrade in hardware capabilities for managing the process of condition data collection and transmission and the development of advanced methods for condition data management, processing and analysis, including machine learning and decision support tools, compose the framework for the current state of the art in condition monitoring within e-Maintenance. Empowered by wireless communications and networking, maintenance tools are made available in the form of flexible web-services, delivered to multiple device types, including tablets and other portable computing devices, while e-collaboration methods enable greater information and knowledge sharing, facilitated by the infrastructure of an e-Maintenance network (Figure 1).

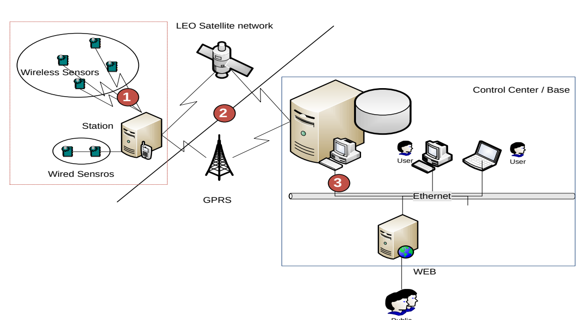

Figure 1: E-maintenance network

This paper presents technological developments that support the integration of e-Maintenance components by distributing monitoring and detection tasks to an ad hoc network of wireless sensor nodes. It is argued that the delegation of computing tasks to a lower physical level of data generation and processing, coupled with elements of learning and intelligence can upgrade the efficiency of condition monitoring infrastructure, while maintaining great deployment flexibility. Our research builds on earlier development of wireless sensing solutions (Emmanouilidis, Katsikas and Giordamlis, 2008) and a structured approach for incremental learning that takes advantage of increasing availability of condition monitoring data to support event detection and diagnostics (Emmanouilidis, Jantunen and MacIntyre, 2006). Within an e-maintenance architecture (Pistofidis, Emmanouilidis, Koulamas, Karampatzakis, & Papathanassiou, 2012), our reported work focuses on upgrading the capability of hardware-integrated solutions to efficiently support wireless condition monitoring by embedding more advanced computational features at the level of sensor nodes.

In Section 2, we present an analysis and brief outline of our development work on distributed and wireless condition monitoring. Coupling the computational capabilities of sensor nodes with machine learning features compose a powerful framework for implementing distributed and intelligent wireless condition monitoring, which pose new challenges for integrated learning capabilities in sensor nodes. These challenges are discussed in section 3. The concluding remarks are summarized in section 4.

2. DISTRIBUTED WIRELESS CONDITION MONITORING

2.1. Condition Monitoring and Wireless Sensing

CBM seeks to perform an early detection of deterioration and potential malfunctions to guide maintenance activities decisions. The asset is maintained or repaired as soon as some machinery condition parameters are detected to exceed a normal or expected range of values. Acting upon the detection and diagnostic recommendations, prognostics seek to determine the most probable time of failure in order to properly schedule preventive actions (IAEA, 2007), reducing costs and increasing quality and profits. Condition monitoring functions by acquiring data that relate to parameters, which constitute indicators of machinery condition. Among the typically measured physical parameters are temperature, pressure, voltage/current/power, RPM, torque, acceleration/Velocity/displacement.

Our reported work deals with the development and integration of more advanced features that leverage on the capacity of wireless sensor networks to delegate computing at the sensor node level. We distinguish two categories of such advanced features, namely:

- Level 1: Data enrichment and pre-processing. In vibration monitoring, these include pre-processing of the original time series to produce transformed representations in new domains, typically in the Frequency (spectrum), quefrency (cepstrum), or even joint time-frequency representations (e.g. wavelets). Even before such transformations take place, pre-processing such as filtering and smoothing is needed, while the spectrum is best estimated after some windowing function is applied to reduce spectral noise. Event detection and diagnostics applied on the transformed signal is still a hard problem. Feature extraction is applied at the pre-processing level to yield specific parameters that when considered independently or most commonly jointly, are more likely to yield discriminatory information and this aid the detection and diagnosis tasks. A word of caution is applicable here, as even the most informative parameter, when considered in isolation, may not provide sufficient information, whereas a parameter not-directly associated with the expected detection outcome may still convey crucial information. It is the combination of individual features that often conveys adequate discriminatory information, rather than the individual features themselves (Emmanouilidis, Hunter, MacIntyre and Cox, 2001).
- Level 2: Event detection and diagnostics. Acting upon extracted feature set combinations, rather than either on the original time series or individual features is recognized as the key to performing efficient event detection and diagnostics. Although it is possible to set simple alarm levels on parameters (e.g. vibration amplitude at a certain frequency or the overall RMS vibration in a frequency band exceeding a certain level), these constitute primary but not sufficient indicators. One reason for that is the cautionary remark mentioned earlier. But another important one is that is that machinery malfunction manifests itself in different ways, even for the same equipment type, depending on the actual equipment size, the positioning of sensors on the monitored equipment and even variations in the way the vibration signal propagates through the body of the monitored machinery. It is therefore often important to calibrate any pattern recognition technique applied for detection and diagnostics on the basis of evidence of data and extracted parameters from readings taken from the specific monitored machinery. This is where machine learning becomes important, both for detection, as well as diagnostics tasks.

Wireless condition monitoring solutions typically do not include such processing features, although Level 1 features have long being available and Level 2 ones are have become increasingly available on wired counterparts. In our reported work, Level 1 features are integrated within the wireless sensor network, that is within the sensing node. Based on features now calculated within the sensor node, new computing and machine learning requirements are posed, so as to integrate Level-2 features within the wireless sensing solution. The main requirements for such features, when employed in a wireless sensing solution context is to balance the potentially discriminatory power they may convey (individually or jointly) with low computing requirements. The right trade-off can be achieved by studying the problem at hand, which therefore implies the need to customize solutions by taking actual representative measurements from the monitored machinery.

This is consistent with observations that condition monitoring techniques are more efficient when perfectly tailored for the particular problem and usually when safety, capital value and potential losses in service or production are of critical importance (Holmberg et al., 2010).

2.2. Intelligent Sensors and Distributed Monitoring

Compared to conventional sensors, intelligent sensors are capable of more advanced functions than plain data collection. By combining sensing and computing at the chip level through micro-electromechanical (MEMS) technology and overall advancement in microelectronics, intelligent sensors can perform self-calibration based on the data collected and adaptive threshold techniques may be deployed for a more accurate condition monitoring. An intelligent sensor is perfectly capable of performing advanced data processing and signal analysis in the time and frequency domains. Bringing a network of such sensing nodes together has the potential to greatly scale-up the level of information processing and the impact on the performance of the performed monitoring. The enabling factors for such an upgrade are already in place, as communication between different sensors can be achieved by existing networking protocols. Coupling the networking capabilities with the individual processing power and sensor-embedded learning capabilities bring a major leap in forward for condition monitoring, that of distributed intelligent condition monitoring.

Distributed condition monitoring relies on the individual node's ability to function as an agent. An agent can adjust its functionality depending on its environment variables. The agent perceives its environment via sensors and acts accordingly via actuators. An agent that aims at optimizing certain performance measures, taking the form of an objective function, is called rational (Montoya et al., 2010).

In a sensor network implementation, many intelligent sensors or nodes, work in parallel to perform condition monitoring and notify base stations via a communications infrastructure. The nodes consist of basic components with simple interfaces. However, connected together in a network, the processing performance increases exponentially. The nodes play the role of the agents in a Multi-Agent system and the Intelligence is distributed among them, thus giving rise to a case of Distributed Intelligence (Montoya et al., 2010).

Low cost peripheral / distributed processing capabilities have been already utilized in large industries for many years, following the evolution of microcontroller and specialized distributed control system (DCS) and wired fieldbus technologies. However, the installation costs of complete systems were high mainly due to the sensor and power/communication wiring costs. It is the introduction of low-power and low-cost wireless interfaces and embedded sensors (MEMS) that now widens the distributed intelligence pattern applicability and the architectural alternatives for a basically data collection / health monitoring system. Still, for the definition of a concrete system's distributed architecture, key tradeoffs have to be set among important extra-functional properties such as power, timeliness and communication/processing bandwidth budgets, as well as fault tolerance, availability and installation/maintenance cost characteristics [Giannoulis et al, 2012].

Knowing the non-linear cost increase for a certain improvement in the quality of sampling electronics, as well as the higher energy and performance costs of wireless transmission compared to processing, the principal pattern is to push towards the periphery, functionality blocks such as local signal processing for the improvement of signal characteristics, calculation of reduced size (compared to the raw signal) sets of important properties, information quality improvements by fusion of data from other related sensors or neighboring sensor nodes, and execution of knowledge extraction algorithms, as long as the overall system cost and chosen performance metrics for the required scalability range are better than just sending the output of a block to a centrally located collecting, storage and processing system. [Pistofidis et al, 2012].

2.3. Signal Processing

Any intelligence built-in a sensor network has to be based on a primitive set of digital signal processing capabilities of the node's microcontroller and its A/D converters. Although such processing may be trivial for wired solutions, only limited such work has been reported as integrated in wireless condition monitoring implementations. Next we present such features built in our wireless condition monitoring implementation.

2.3.1. A/D Converter's Characteristic Improvement

The A/D converter's precision and integral nonlinearity (INL) factor affect the effectiveness of the node. For 4-20 mA current loop measurements poor, linear behavior of the A/D converter can lead to inaccurate results. In our approach, before initialization of the node's main functionality, the first step of an intelligent sensor should be the linear improvement of the A/D converter's characteristic. An external well-designed D/A converter can be used as the force of calibration by feeding the A/D converter with key values used for calculating the A/D converter's output differences from the expected values. The flow diagram in Figure 2 describes the calibrating procedure before the main functionality of the intelligent sensor (Texas Instruments, 1999).

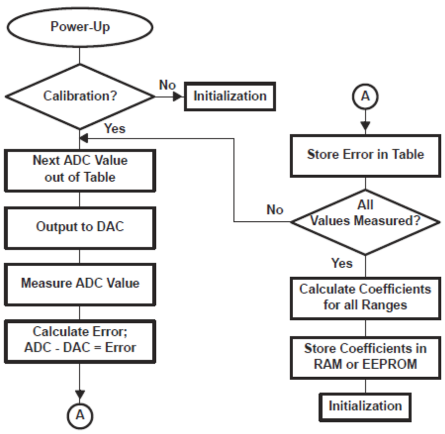

Figure 2: Calibration with an External D/A Converter

2.3.2. Signal Smoothing

In many cases, in order to make decisions from observing or processing the measured data, or to capture important patterns, signal smoothing might be useful in order to cancel out spikes and noise in the data set and generally increase signal-to-noise-ratio. For this purpose four techniques are considered depending on the applications:

- Low-pass digital filter.
- Exponential moving average, with which the applied smoothing percentage (alpha parameter) can be controlled and no particularly large window is needed for smoothing.
- Moving median with a 3-sample window, with which a substantial smoothing is achieved with the profound elimination of undesired spikes.

Figure 3 shows the effect of applying an exponential moving average (alpha parameter = 0.15) and a moving median filter on raw data.

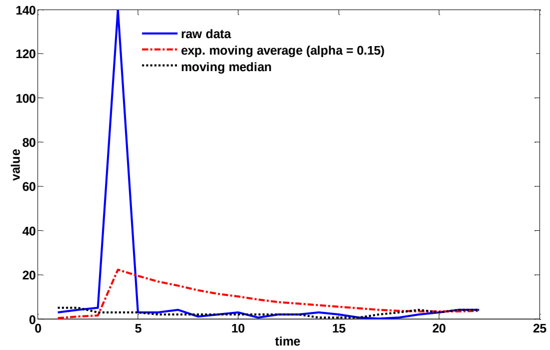

Figure 3: Exponential Moving Average

- The Savitzky–Golay filters are low- pass filters that smooth the signal with the use of local least-squares polynomial approximation. The main asset of this type of filters is that they smooth noisy data, while preserving the shape and height of the peaks and spikes (Schafer, 2011).

2.3.3. Vibration Analysis

In our approach, for the purpose of vibration analysis, the accelerometer's data is collected by the A/D converter and via the microcontroller's DMA controller, is saved in RAM at a sampling rate much greater than the Nyquist rate. Upon completion of the collection, the microcontroller's CPU is interrupted and a series of actions take place:

1. DC bias removal, by subtracting the mean value from each data sample.
2. Filtering the data with a window function, Hanning, Hamming, Blackman or Bartlett. The aforementioned window functions are quite effective and require less computational complexity that others, as shown in table 1 (LDS Inc., 2003).

Table 1: Window comparison

Window	Best for these Signal Types	Frequency Resolution	Spectral Leakage	Amplitude Accuracy
Barlett	Random	Good	Fair	Fair
Blackman	Random or mixed	Poor	Best	Good
Flat top	Sinusoids	Poor	Good	Best
Hanning	Random	Good	Good	Fair
Hamming	Random	Good	Fair	Fair
Kaiser-Bessel	Random	Fair	Good	Good
None (boxcar)	Transient & Synchronous Sampling	Best	Poor	Poor
Tukey	Random	Good	Poor	Poor
Welch	Random	Good	Good	Fair

3. Calculating the FFT of the filtered data, using a recursive radix -2, out-of-place algorithm or an in-place

algorithm with bit- reversal permutation, depending whether the goal is speed or memory efficiency.

4. Calculating the amplitude of the complex numbers that were the result of step 3, thus providing the amplitude response. Results are buffered and sent to the network coordinator or base station via a communication protocol implemented in the nodes' firmware. Figure 4 shows an 8-kHz, 128-sample sine wave from a waveform generator, filtered with a Hanning window and figure 5 its amplitude response.

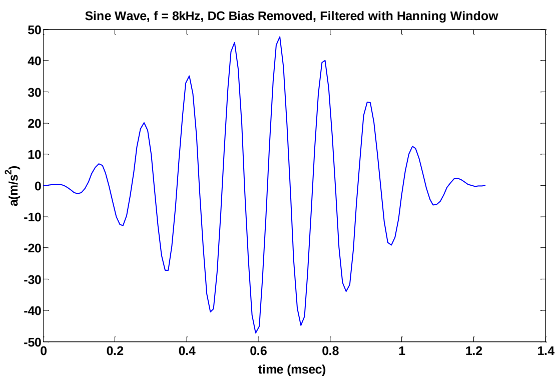

Figure 4: 128-sample sine wave, 8 kHz, filtered with Hanning window

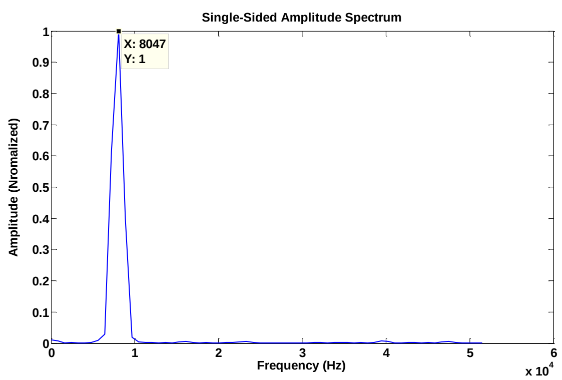

Figure 5: Amplitude response of a 8-kHz 128-sample sine wave

5. Calculating velocity by integrating acceleration (figure 6), using the cumulative trapezoidal rule, as shown in figure 7. The resulted outcome is buffered and sent via communication protocol to the network coordinator.

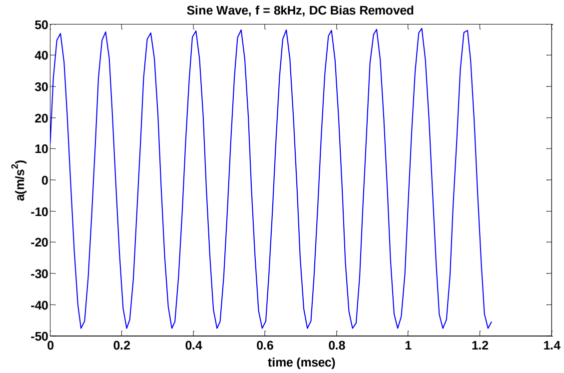

Figure 6: acceleration, raw data after DC bias removal

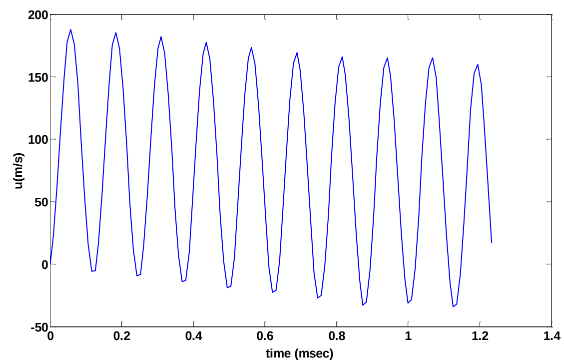

Figure 7: Velocity, output from cumulative trapezoidal rule

2.3.4. Periodicity Detection

Periodicity detection is a powerful mining tool in automotive, aviation and manufacturing industries for condition monitoring. All rotating parts of machines can be studied and a change in the periodic structure of the machine vibrations can be detected for the prevention of machine wear or potential failure (Vlachos et al., 2005).

Two basic tools combined together provide information on periodicity: FFT for potential periods or period hints and autocorrelation for the verification of these period hints (Vlachos et al., 2005).

FFT gives the amplitude frequency of the signal and by setting an amplitude threshold, any frequency exceeding that threshold, becomes a hint. Figure 8 shows a superposition of two sine wave signals, with frequencies of 40 kHz and 80 kHz respectively. Figure 9 shows the amplitude response and the two main signal frequencies. By applying a desired threshold, these two frequencies or periods are selected as hints. The threshold setting algorithm could begin with an initial high value for the threshold and gradually decreasing it with a certain step. More advanced adaptive threshold algorithms could be implemented. Finally, the period hints are compared to the values that represent the autocorrelation hills and if the hints and the hills are equal or if they differ at a maximum of 30%, then the detected periods are the time values of the hills, thus refining the period hints (figure 10).

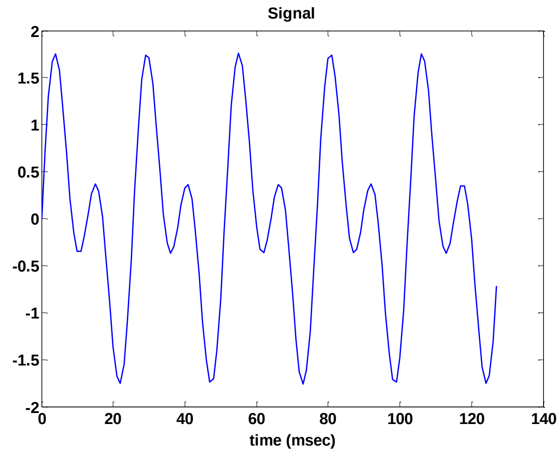

Figure 8:Signal for periodicity detection

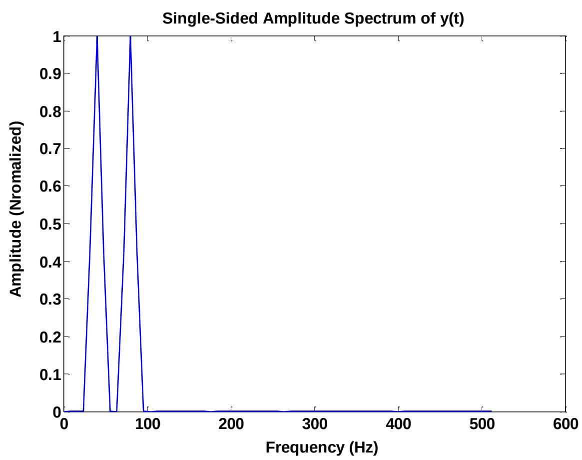

Figure 9: Amplitude Response

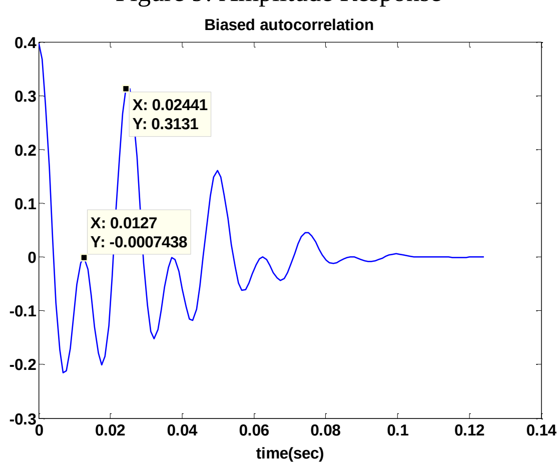

Figure 10: Biased Autocorrelation, two dominant periods verified and refined

2.3.5. Novelty Detection

An algorithm has been designed and developed to detect absolute differences between consecutive samples, that exceed a specified threshold and that may be crucial. The algorithm classifies the detected novelties into *spikes*, if there is a sudden change and return to normal and *stage changes*, if a more permanent change occurs and the values thereafter belong to a different range. The algorithm also calculates the time of occurrence, duration of these novelties, starting and ending values for state changes, starting and maximum values for spikes. The threshold setting algorithm begins with an initial high value for the threshold and gradually decreases it with a certain step, as in the case of periodicity detection. The initial value or upper threshold limit (UTL), as well as the final value or lower threshold limit (LTL), are automatically set with the use of Eq. (1) and Eq. (2) (Bakar et al., 2006):

$$UTL = m + 3\sigma/\sqrt{N} + m - 3\sigma/\sqrt{N} = 2m \quad (1)$$

$$LTL = m - 3\sigma/\sqrt{N} \quad (2)$$

where,

m = mean value of data samples

σ = standard deviation of data samples

N = total number of data samples

Figure 11 shows engine turbo charger RPM raw data and figure 12 the novelties detected by the algorithm. Dashed - line novelties are classified as spikes and dotted - line novelties as state changes. Figure 13 shows the results of the algorithm when applied on draft force measurements. Because of the noisy nature of these measurements, Savitzky- Golay filtering is applied before the algorithm and the new results are shown in figure 14, where the most important novelties now stand out. The classification is parameterized and state changes can be considered as spikes, by altering a parameter that affects the time duration of a spike. Figure 15 shows this effect. Especially, the state change that appeared at the 500-700 time unit range of figure 14 is now classified as spike in figure 15.

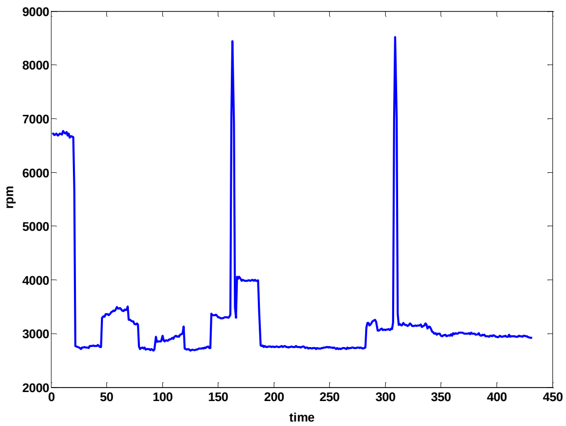

Figure 11: Main engine turbo charger RPM measurements

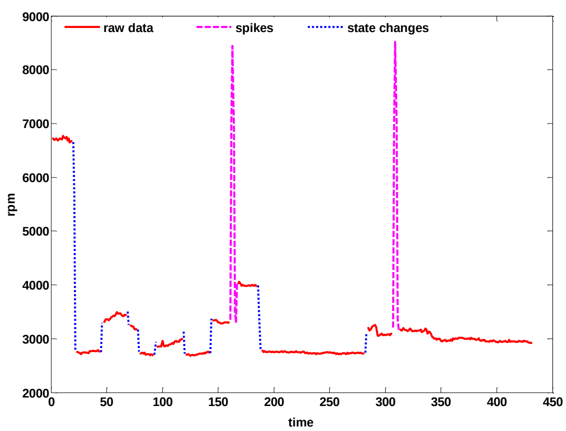

Figure 12: Main engine turbo charger RPM Novelties detected

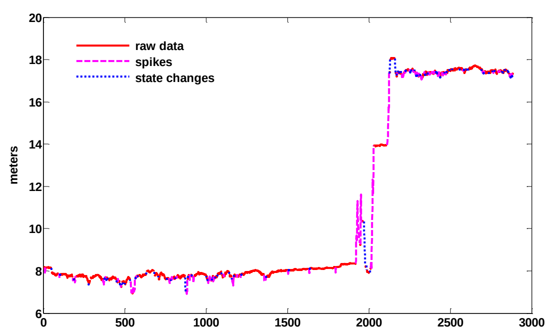

Figure 13: Draft force novelties detected

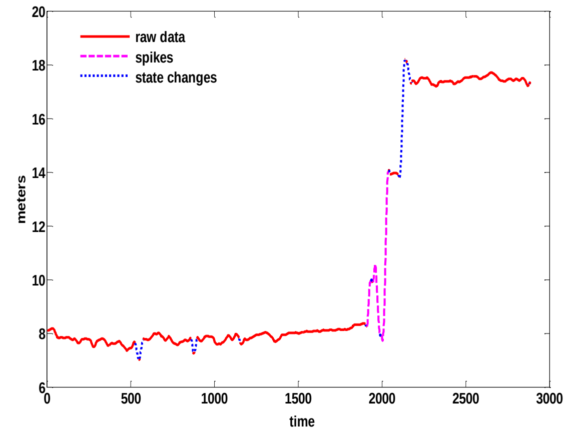

Figure 14: Draft force novelties detected after Savitzky-Golay smoothing

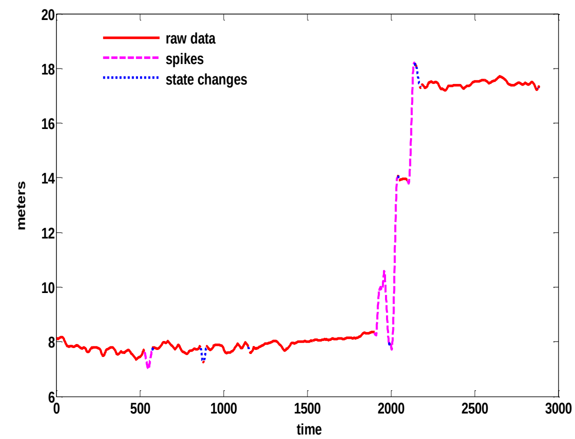

Figure 15: Resulted graph after increasing the spike width parameter

3. FURTHER WORK

The next and most intriguing element of an intelligent wireless sensor network is the ability of learning. Learning is the added value of an intelligent sensor that leads to higher levels of decision-making and guidance for the maintenance manager. This is an on-going activity and our considerations cover two categories of Machine Learning: Classification and Clustering, which are further described as supervised or predictive and unsupervised or descriptive learning respectively.

Supervised learning uses a known data set to make predictions and to classify an unknown data object based on a model derived from the training set. In other words, the training set consists of pre-classified patterns and the goal is to label a new and unlabeled pattern. The model is derived from the use of the pre-classified patterns as the basis for learning the class descriptions, which in turn are used for the classification of new data. (Jain et al., 1999). An effective method under consideration is the *Naive Bayes Classifier*, because of its over-simplified assumptions and, yet, very positive outcome (Katsouros et al. 2013). This classifier is based on Bayes' theorem -from statistics theory- and produces results regardless of the presence or absence of a particular feature of the class (Murphy, 2012).

On the other hand, unsupervised learning makes predictions about unknown data without any training set, whatsoever. Its purpose is to discover interesting patterns in the data, a concept called *Knowledge Discovery* (Murphy, 2012). This form of data analysis can be realized with *Cluster Analysis* or *Clustering*, where the decision is to allocate patterns in known clusters or even form new clusters when this assignment does not appear to be credible. This approach can be applied to event detection. When readings and consequently a set of features are assigned to known clusters, then the condition state of monitored machinery can be said to belong to a known condition (Emmanouilidis et al., 2006). Typically this belongs to a normal operating condition. Depending on the problem formulation it may also belong to an unknown condition. Using the terms 'known' and 'unknown' here imply the association of a known condition with a condition for which representative readings have already been recorded. An unknown condition for the monitoring system is one that representative readings have not been recorded yet. This is an essential level of processing for event detection.

A detected event may either correspond to a situation where an unknown condition has been detected, or to one that a measurement is assigned to an abnormal condition, on the basis of pre-existing evidence. Clustering therefore can offer this first level of processing, that is essential of any event detection mechanism. Once data is assigned to 'unknown' category, the next step is to perform data labeling, that is to label the newly formed cluster by assigning it to a certain condition. There is a wide range of clustering techniques that can be applied in such tasks. In all cases a critical issue to be addressed is to define an appropriate distance metric, such as the *Minkowski metric*. Nonetheless, in many cases the set of parameters upon which a decision has to be reached can be of very heterogeneous nature and in such cases other heterogeneous distance metrics, such as *Hausdorff* distance may be applicable (Jain et al., 1999).

4. CONCLUSION

This paper presented work that achieved to upgrade the capability of hardware-integrated solutions to efficiently support wireless condition monitoring by embedding more advanced computational features at the level of sensor nodes. We have presented the trends and progress in the intelligence of wireless sensor networks and have proposed some key points that contribute to this concept and to the evolution of e-maintenance. It is our belief that the integration of such potent hardware solutions in wireless condition monitoring, with advanced signal processing and learning features has the potential to offer a significant upgrade in the ability to deliver distributed and intelligent wireless condition monitoring solutions. Such developments would constitute a powerful addition to the e-maintenance solutions and are being developed as part of an e-maintenance platform that aims to provide technical or managerial staff with smart choices and solutions, as well as valuable information and services at any point in time, leading to higher confidence in decision-making processes and improved maintenance performance.

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