A Smart Modular Wireless System For Condition Monitoring Data Acquisition

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Abstract

Smart sensors, big data, the cloud and distributed data processing are some of the most interning changes in the way we collect, manage and treat data in recent years. These changes have not significantly influenced the common practices in condition monitoring for shipping. In part this is due to the reduced trust in data security, data ownership issues, lack of technological integration and obscurity of direct benefit. This paper presents a method of incorporating smart sensor techniques and distributed processing in data acquisition for condition monitoring to assist decision support for maintenance actions addressing these inhibitors.

1. Introduction

Common practices in condition monitoring of the shipping industry have been resilient to change as the industry in general is often reluctant to engage new technologies and computerised systems, DNV GL (2014). Several barriers are often recognised with the most prominent being trust in the technology, security, proprietary data and ownership as well as data transferring to shore, DNV GL (2014), Latarche (2015). One of the main drivers also is that the direct benefit of implementing such technologies is not clearly identified by several key stakeholders in the ship operator or ship owner organisations, Adamson (2016a). However, despite the barriers, in 2015 Big Data growth and importance for the industry has exceeded their predicted trends, Adamson (2015). In that respect, an increasing need is expected for systems that manage and translate the collected data to information that is relevant and useful for the industry.

An area that is particularly expected to generate a large amount of data in the upcoming years is Condition Monitoring (CM). As more ships embrace the continuous monitoring approach the influx of data is expected to exponentially increase. Several technological advances relevant to CM include smart sensors, distributed data processing and the cloud. However, systems that utilise these are not yet widely available in the shipping environment.

The system presented in this paper is based on a smart sensor technique and distributed processing for condition monitoring. Also, it introduces the concept or sensor-servers. The sensors utilised are well established technologies in the condition monitoring sector for marine engines. The presented system's approach is in collecting and pre-processing data relevant to vibration, temperature and pressure prior to wirelessly transmitting it to a central collection point onboard a vessel. Moreover, the smart collection unit (SmartDAQ) is able to derive events from the data at the remote location; thus, prioritising messages based on importance. This reduces the amount of transmitted data and also power required to operate the wireless communications chip. Furthermore, it tackles some of the most prominent issues with modern wireless data recording systems such as false data and gaps in data streams finding their way into the database. The data is then post-processed to assist decision support (DS) for maintenance actions that engineers can take onboard the vessel. These actions are suggested by the DS software based on the recorded condition. The system has the capability of connecting to a server based database allowing secure data transfers to shore over the internet for further processing if required.

As the system is based on a modular approach in both the components and the algorithms developed, it is able to support integration of new technologies and provide a base for future large scale systems.

Hence, answering an existing need for low cost platforms for both academic and industrial projects. For example, as the Cloud matures and internet on ships becomes a lower cost commodity – Satbeams (2017), Adamson (2016b) – the system could incorporate a new module that allows for reliability analysis to take place on the cloud instead of the local computer onboard the ship. In fact, any substitution of any of the algorithms could be performed independently of the rest of the system thus providing an ideal ground for development and expansion.

The following sections will present the methodology (Section 2), followed by the description of the integrated system (Section 3) and the implementation strategy (Section 4). Then section 5 will present a case study with results presented in section 6. Section 7 will discuss related work. Finally, section 8 will conclude this paper.

2. Methodology

This section presents the methodology followed to develop a novel system that satisfies the industry requirements presented in the previous section. A Systems' Engineering approach was followed in developing the methodology, INCOSE (2016). This approach was further extended to incorporate all the requirements of the system as well as a thorough academic approach and is presented in Figure 1.
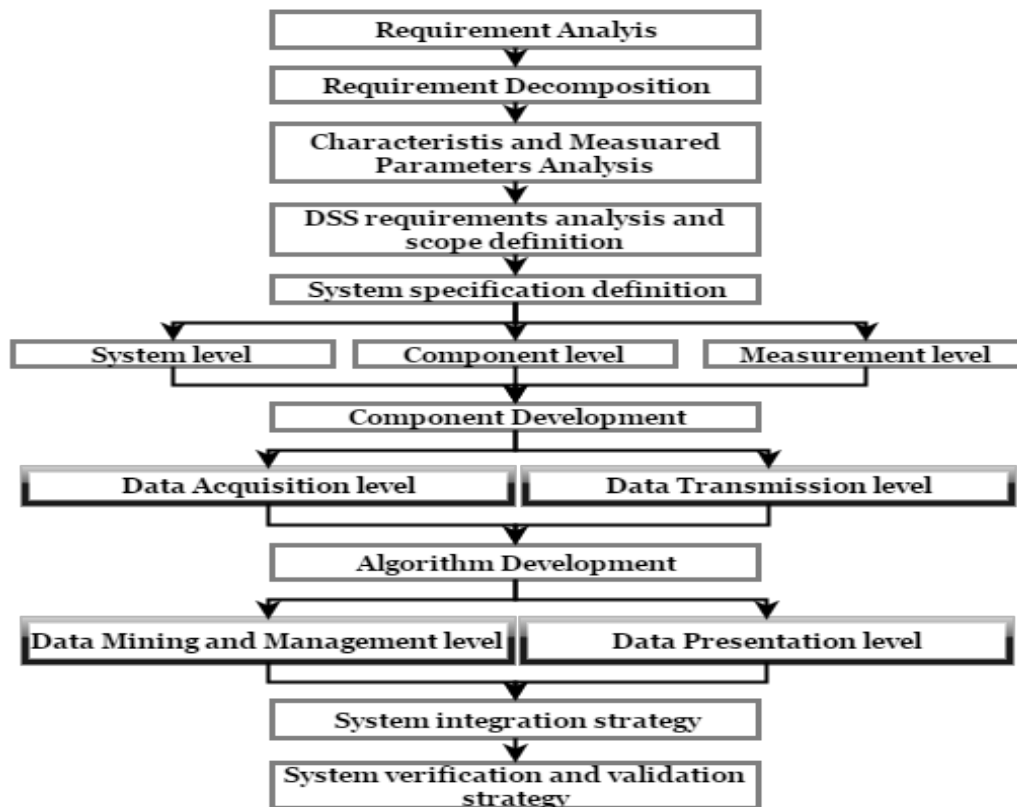

Fig.1: Methodology

Initially a thorough analysis for the requirements was performed which was based on the outcome of a critical literature review of the condition monitoring solutions and research approaches available in shipping and other industries. The key findings of the literature review demonstrated that there is a lack of large scale strategy for whole ship CM and that there is a slow industry uptake mainly due to cost versus benefit barriers. More specifically, system requirements were identified as allowing a large variability of monitoring objectives through a modular approach, providing a low-cost capital investment solution while making the direct benefit and impact more prominent and relevant through appropriate processing and presentation of results. Additionally, reduced personnel training was an identified requirement. Finally, the system must provide an output that is easily integrated with a

variety of maintenance strategies but ultimately provides better Class Condition, reduces maintenance costs and has a positive impact on energy efficiency, Michala et al. (2015), Michala et al., (2016). Thus, a large complex system is required to provide a suitable and feasible solution to satisfy these requirements.

Based on the analysis of existing CM approaches as well as commercial systems the minimum measured parameter requirements include vibration, pressure and temperature. Also, the ship movement profile should be recorded so that changes in the data can be correlated to the speed and weather conditions extrapolated from the three-axis acceleration and rotation of the ship. Finally, speed is an often recorded parameter for rotating machinery but as vibration is recorded this was considered a secondary requirement to be added to the system on a later stage.

Based on the requirements for identifiable and direct benefit of CM, the proposed system incorporates a Decision Support System. As such, the relevant information extracted from the data can be used to directly affect the maintenance actions and at the same time relate the condition of the ship to cost. For example, reduced performance from degradation of a specific component can be quantified as cost due to underperforming. In that respect, a strategy that commands high performance could utilise the DSS to estimate which maintenance actions would increase the performance of the ship. Performance is also directly affecting energy efficiency so DSS output with high performance costs would also indicate high energy related costs. Overall, the correlation of condition to cost can prove useful for not only the day to day operation but the overall long term maintenance planning and scheduling strategy. However, there is a minimum amount of monitoring requirements that is necessary for the DSS to provide accurate output. This includes monitoring of the main engine's fuel oil, cooling and lube oil system as well as bearings and where applicable the turbo charger. Moreover, bearings of the propulsion system and auxiliary engines would be important to increase the relevance and accuracy of the DSS. As the system is modular though, a smaller set of components could be initially measured. However, such an option would only be able to provide relevant information for part of the ship's machinery and equipment.

Considering the requirements, measured parameters and DSS requirements the specification definition identifies the most appropriate system as a modular versatile system that has four main layers. The first layer is data acquisition and includes the SmartDAQ component that is presented in the following section. The second layer is the data transmission for which a wireless method was selected. Then there is the data management and mining layer that describes a two phase of pre and post transmission processing and a system for data management that is also presented in the following sections. Finally, the last layer is the data presentation which is the DSS system, also presented in the next section.


3. Smart Modular Wireless System

The outcome of the development process based on the above specification is presented in Figure 2. The integrated system is comprised of two physical components, the SmartDAQ component and the receiver unit. In terms of software architecture there are four main components. The pre-processing component, the Finite State Machine (FSM) monitoring and control component, the post-processing component and the reliability, DSS and transmission to shore component.

The Smart DAQ component is comprised of a set of analogue electronics that collectively provide the signal conditioning necessary for valid input to the system, an Embedded Linux Platform and a wireless transmitter. The analogue electronics configuration (Figure 2.a) was developed so that it could be printed on a Beaglebone Black (BBB) cape. On the other hand, the Receiver Unit is comprised of a receiver and a connector to the local PC which is available in the control room. At this point it is assumed that the receiver is in the control room.

By distributing data processing a Cloud inspired approach provides the ability to harness processing power at the edge of the network in a sensor-server fashion. The network of SmartDAQ units can

utilise the high processing capabilities of the embedded Linux platform and at the same time minimise the message load of the wireless transmission channel. In that respect, the cross-talk noise between the nodes of the network can also be minimised providing better Quality of Service (QoS). The pre-processing component is an information extraction mechanism that has two main targets:

1) to capture mean, standard deviation or Fast Fourier Transform of the recorded signal and

2) to record events. Events are data points that are outside the "normal" expected range and identified as alarm conditions. Alarm conditions can be either values indicating the necessity of immediate crew action or conditions indicating that the machinery/equipment is not in operation.
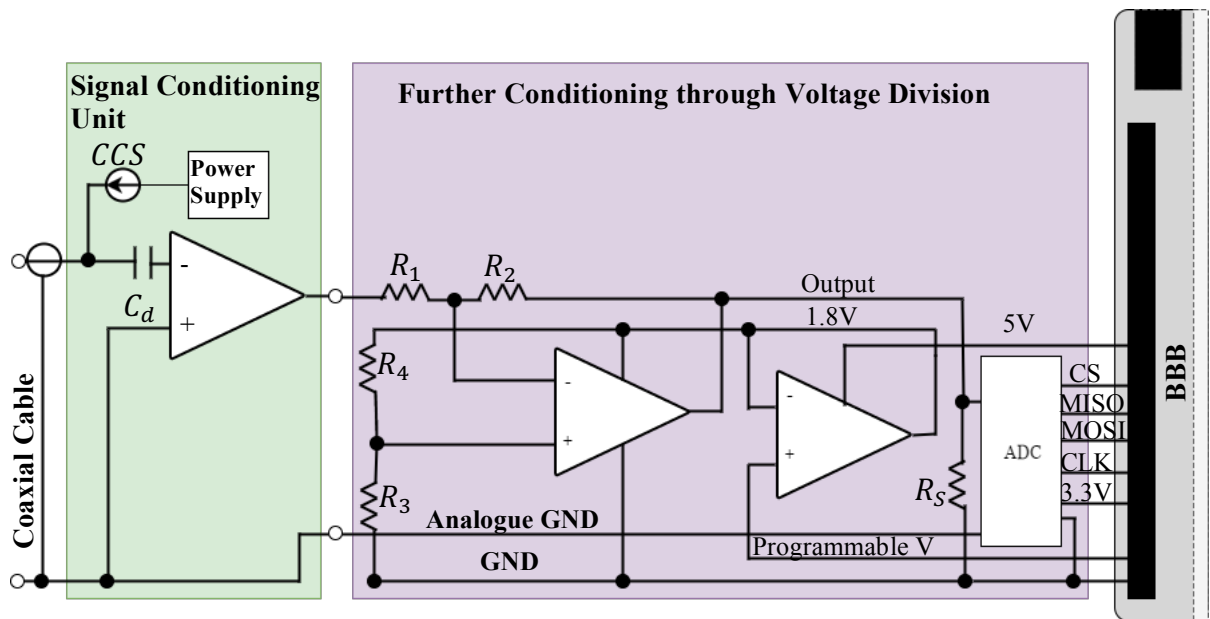
(a)
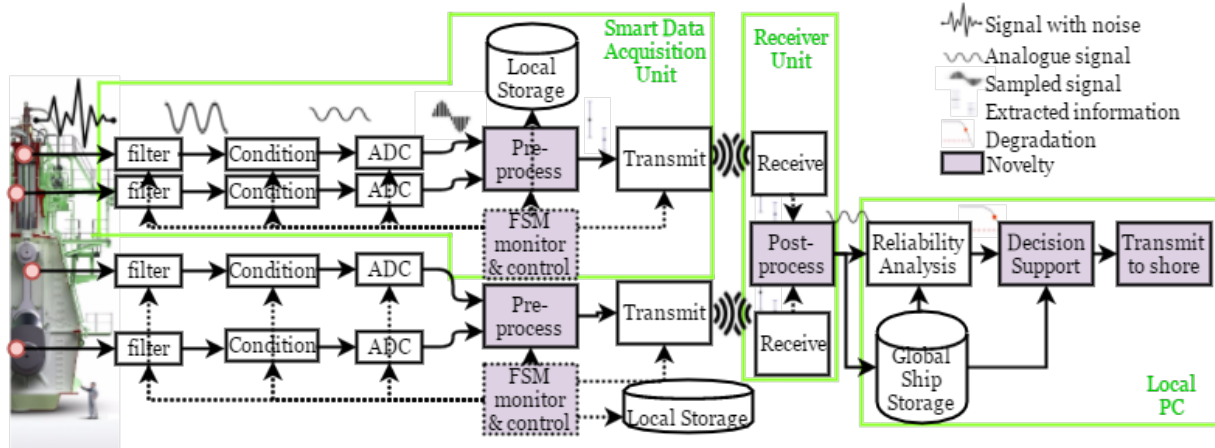
(b)

Fig.2: SmartDAQ (a) and Integrated System (b)

To meet requirements of power consumption the FSM, monitoring and control unit oversees the operation of the Smart DAQ component. The FSM is presented in Figure 3. Moreover, the system can be contacted from the main collection point with commands that allow the central node to monitor the condition of the network, the statistics of network operation and the error conditions of the Smart DAQ. Finally, the central collection point is able to send commands to each Smart DAQ that allow for the maintenance of the wireless network including healing, removing nodes and forcing the FSM into certain states. This way a remotely located user with appropriate access rights can manage the

network without necessitating physical interaction with the Smart DAQ component.
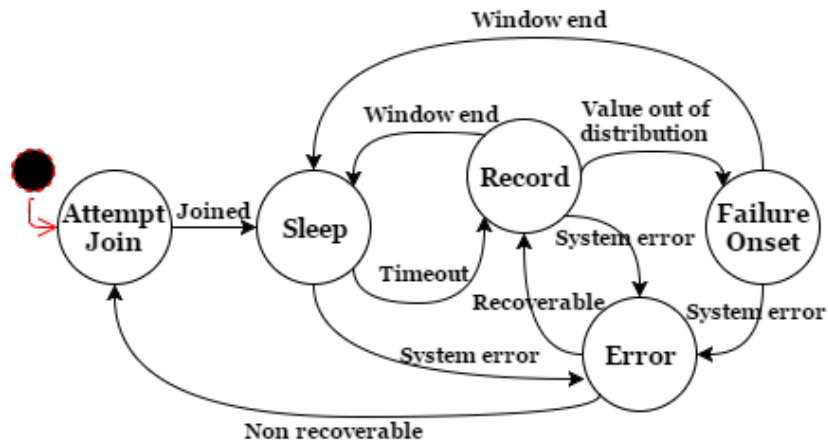

Fig.3: Smart DAQ state machine definition

The post-processing component manages the incoming information and is tasked with providing an output that is similar to the initial data stream recorded by the sensor. In that respect, the pre-processing component is hidden to any components requiring the output of the post-processing component. That isolates the physical components and their particulars. The output of the post processing component can be used by any existing analysis method already available. However, this paper proposes an analysis that provides suitable DSS input to the identified requirements.

As part of the proposed system the MRA tool presented in the INCASS project was used for the next step of the analysis of the post-processing output, INCASS (2015). This tool accepts input as raw data which is here provided by the post-processing component and through reliability analysis produces degradation per failure mode per ship machinery/equipment system, sub-system and component. This tool is particularly useful as the output is suitable input for the DSS component. The degradation and association to failure mode is crucial for the identification of relevant maintenance action. However, it requires special training of the crew in order to understand this information and translate it to relevant actions. Therefore, the reliability analysis tool is necessary for the system but the DSS component enhances the system as it is able to directly demonstrate tangible benefits to the user without mandating any training. Thus, satisfying one of the identified requirements.

As a first step the DSS tool identifies which machinery/equipment components are more likely to demonstrate degradation in the forecasted period and priorities them according to likelihood. A system of weighted probabilities is used for this classification as described by Equations 1 and 2 below.

$$W_{c_k} = \frac{L_{c_k}}{\sum_{i=1}^{m} L_{c_i}} \qquad (1)$$

Where W_{c_k} is the weighted contribution, $k = 1 \dots m$ and m is the number of components contributing to the sub-system under investigation.

$$N_j = \frac{L_j \times W_{c_x}}{\sum_{i=1}^{n_1} L_i \times W_{c_1} + \sum_{i=1}^{n_2} L_i \times W_{c_2} + \cdots + \sum_{i=1}^{n_m} L_i \times W_{c_m}} \qquad (2)$$

Where N_j is the contribution of the failure mode $j = 1 \dots l$ and l is the total number of failure modes of all the components contributing to the sub-system under investigation, m is the number of components contributing to the sub-system under investigation, W_{c_x} is the weighted contribution of the component under which failure mode j is listed and $n_1, \dots, n_m$ are the numbers of failure modes

listed under each component $c_{k=1\dots m}$.

As a second step the DSS further processes each of the components expected to have failures and identifies the optimal action to suggest. The optimisation is formulated as a multi-objective multi-constrain problem. The failure mode set $M_h = \{m_1, m_2, \dots, m_n\}$ and the action set $A_h = \{a_1, a_2, \dots, a_g\}$ associated with a failure mode of component/subsystem/system $K_h \in K$ were defined where K is the set of monitored components, subsystems and systems on the ship. The function $L(a, m)$ is true if an action a is associated with a mode m. Also the set of available parts $P_h = \{p_1, p_2, \dots, p_j\}$ associated with K_h was defined. The function $U(a, p)$ is true iff a part p can be used within action a in order to perform the action successfully.

The problem is to find a feasible solution to the partial function F (Equation 3). Where $E = \{a_1, a_2, \dots, a_l\}$ is the set of actions for which there are expertise available on the ship and $W = \{a_1, a_2, \dots, a_z\}$ the set of actions that can be executed under the particular weather conditions. F is an assignment of actions for each component/subsystem/system while obeying the constrains. As F is a partial function the actions that belong to the domain dom(F) are the selected actions. The constrains of the system are expressed in Equations 4 and 5. Also the secondary objective is the minimisation of Equation 6.

$$F: A_h \to \{E, C\} \to L \wedge U = 1 \qquad (3)$$
$$\forall a_i^h, a_j^h \in A_h, \left(a_i^h \in \text{dom}(F) \wedge a_j^h \in \text{dom}(F) \right) \Rightarrow i = j \qquad (4)$$
$$\forall a_i^h \in A_h : \left(L(a_i^h, m_i^h) \wedge U(a_i^h, p_i^h) \wedge \left(\exists\, a_i^h \in E \cap W \right) \right) \Rightarrow a_i^h \in \text{dom}(F) \qquad (5)$$
$$\min(C_T) \qquad (6)$$

Where $C_T = C_E + C_S + C_A + C_M + C_P + C_C$ but the individual costs may have competing conditions. The sub-costs are relevant to company costs originating from 'Environment' (C_E) regulation related charges, 'Safety' (C_S) related charges, 'Asset' (C_A) purchasing, 'Maintenance and Operation' (C_M), 'Performance' (C_P) and 'Commercial Penalties' (C_C) related to delays in delivery amongst others. The optimisation computation provides an initial allocation of optimum action suggestion. However, as the system records more information it is able to adapt to actions that have been successful in demonstrating a beneficial correction to the degradation curve. This is achieved through a machine learning algorithm presented in Figure 4.
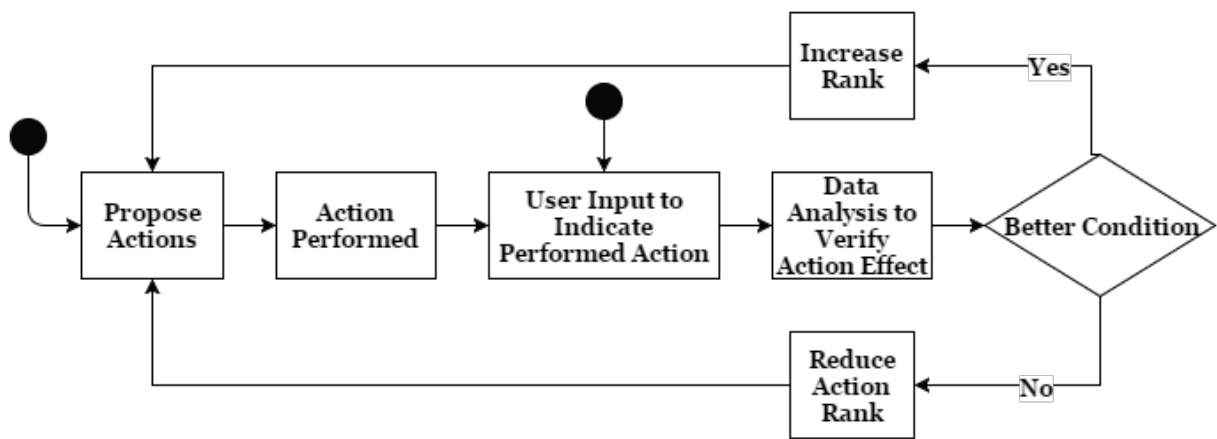

Fig.4: Adaptive action suggestion based on collected information.

5. Case study

The case study presented in this section is concerned with demonstrating the systems capability of managing large load of recorded data. To evaluate the load handling capabilities of the system the

performance of the network is recorded in regards to the number of attempts required for a message to be successfully delivered. Additionally, this is an indication of the system's reliability as well as the network's QoS. Finally, the secondary objective of this case study is to verify that the data delivered by the post-processing tool to the reliability analysis tool are valid.

To simulate high load, 8 virtual sensors were enabled on each SmartDAQ unit and total of 4 SmartDAQs were deployed (Fig. 5). Moreover, a 5th Smart DAQ was deployed with 6 virtual sensors plus one actual sensor (Fig. 6a). Finally, a single collection point was connected to a PC (Fig. 6b). The PC was updated with the required software components to enable the post-processing, reliability analysis, DSS and transmission to shore components. Virtual sensors were used instead of actual sensors for most of the SmartDAQs in this case study because there were no sufficient number of physical sensors available in the laboratory engine room to provide a significant load to the system. A virtual sensor is a bypass of the signal conditioning hardware as the readings are not sampled from the analogue input of the board. Instead the sampling unit is wired to a board analogue output. An additional component is enabled per sensor to read data from a file and send it to the analogue output. The system operates as if it was reading an actual wired signal through the analogue input. Hence, the process is imitating an actual sensor connection and respects the integrity and coherency of the presented system components. Each Smart DAQ was housed in a small non-metal box to protect the wiring (Fig. 5a, 5b) apart from the one connected to the actual sensor (Fig. 6a).

(a)   (b)

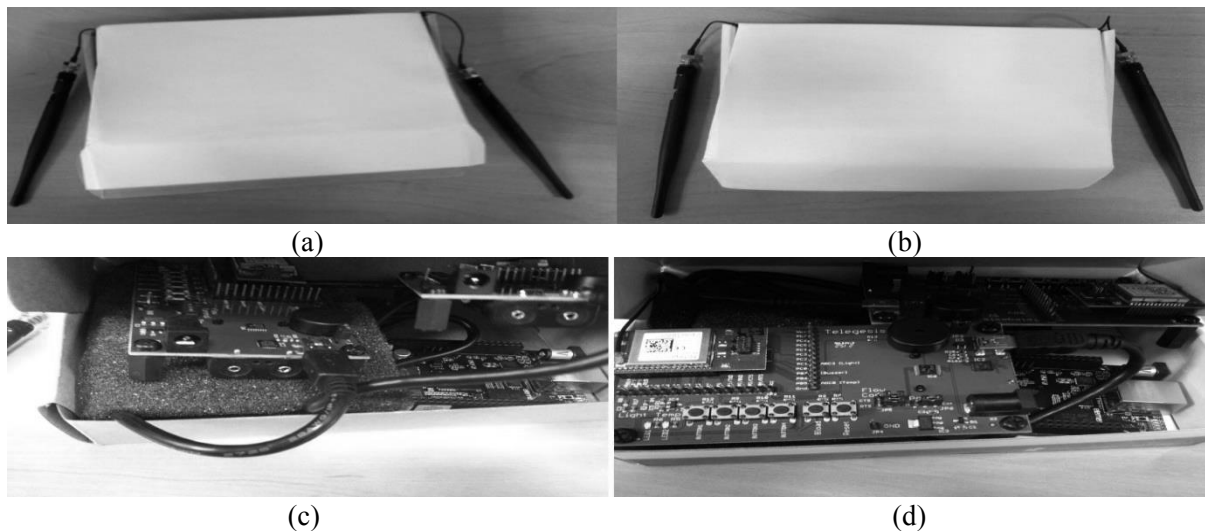(c)   (d)

Fig.5: Four SmartDAQs with virtual sensors: (a) and (b) housing and antennas, (c) and (d) wireless transmitter development boards and embedded Linux boards, battery powered.
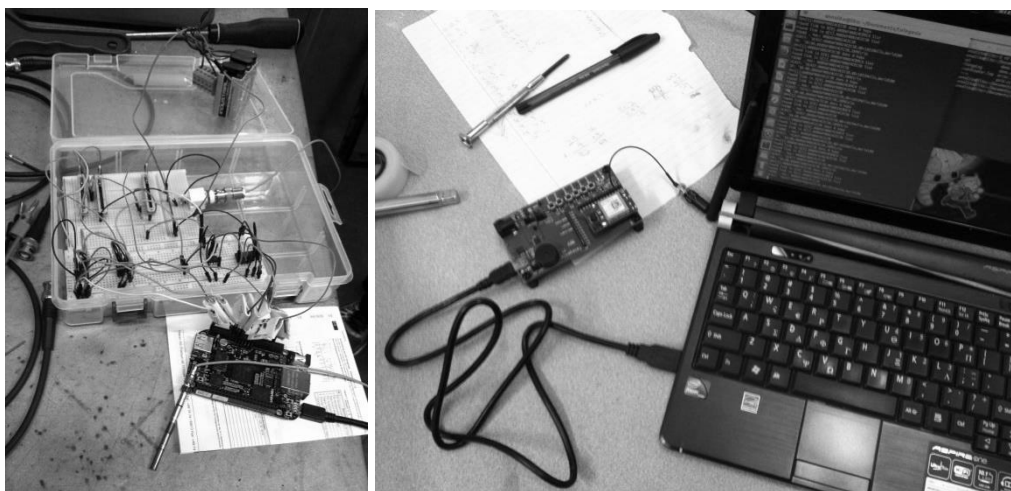

Fig.6: Board connected to signal conditioning circuit and sensor (left) and receiver board connected to local PC (right).
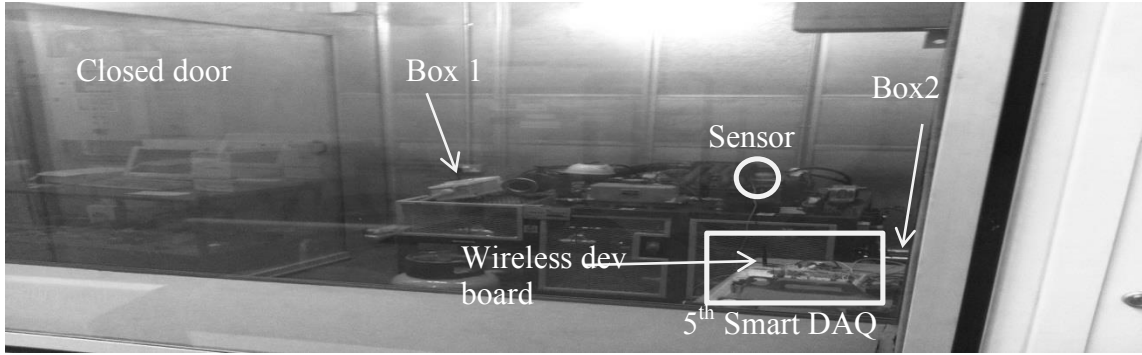
Fig.7: Deployment in Engine Laboratory, image captured from control area through the glass window.

The installation at the laboratory engine room allowed for all 5 Smart DAQs to be deployed inside the engine room and the collection point located outside (Fig. 7). The engine room is a metal box with a glass window that looks outside to the control area. By closing the door between the engine room and the control area conditions of higher interference from cross-talk noise and reflexion from the metal were generated in the room. The two boxes were installed at the floor behind the engine to increase the distance from the glass window as much as possible and increase the interfering obstacles.

The data supplied to the virtual sensors were data recorded on an existing ship during voyage. In total the 38 virtual sensors corresponded to measurements recorded by actual sensors installed on machinery and equipment of the ship. The list of measurements is presented in Table I. Moreover, the physical sensor was installed to record pressure in one of the cylinders of the engine available at the laboratory. In Table I the temperatures were recorded in degrees ^{o}C and the pressures in Kgr/cm^{2}.

Table I: Measured parameters from ship's main engine

No.	Measurement	No.	Measurement
1	Thrust Bearing LO Outlet Temp	20	IntShaft 1 Bearing Temp
2	TCLO 1 Input Press	21	IntShaft 2 Bearing Temp
3	TCLO 1 Input Temp	22	IntShaft 3 Bearing Temp
4	TCLO 1 Output Temp	23	Main Lube Oil Input Pressure
5	TCLO 2 Input Press	24	Main Lube Oil Input Temperature
6	TCLO 2 Input Temp	25	Cylinder Input JCFW Pressure
7	TCLO 2 Output Temp	26	Cylinder 1 Output Exh Gas Temp
8	Scav Air Manifold Press	27	Cylinder 2 Output Exh Gas Temp
9	Scav Air Rec 1 Temp	28	Cylinder 3 Output Exh Gas Temp
10	Main Engine Start Air Press	29	Cylinder 4 Output Exh Gas Temp
11	Piston CO Input Press	30	Cylinder 5 Output Exh Gas Temp
12	JCFW 1 Output Temp	31	Cylinder 6 Output Exh Gas Temp
13	JCFW 2 Output Temp	32	Cylinder 7 Output Exh Gas Temp
14	JCFW 3 Output Temp	33	Cylinder 8 Output Exh Gas Temp
15	JCFW 4 Output Temp	34	Aft Camshaft Bearing Temp
16	JCFW 5 Output Temp	35	Fore Cam Bearing Temp
17	JCFW 6 Output Temp	36	Exh Gas Output After Turbo Charger 1 Temp
18	JCFW 7 Output Temp	37	Ex Gas Output After Turbo Charger 2 Temp
19	JCFW 8 Output Temp	38	Main Engine Control Air Input Press

6. Results

For the above case study this section presents the results. An analysis of the network performance

demonstrates that out of the 4176 transmitted packets per sensor over a period of one month there were no packets lost. Moreover, the transmission was successfully received and acknowledged in the first attempt for 90.53% of the cases. A second attempt was necessary for 9.09% of the packets while a statistically insignificant 0.38% of packets required three or more attempts. The standard variation was 5.98, 5.85 and 0.41 respectively for each attempt classification. There were no received packets that were delivered out of sequence and all messages were reconstructed successfully for all the sensors. Figure 8 demonstrates the analysis for the 39 sensors where the sensor instance corresponds to the number presented in Table I above for sensors 1 to 38. Moreover, sensor instance 39 corresponds to the physical pressure sensor.

During the test period no interventions were made to the network and one type of event was recorded. This event type was created due to the physical pressure sensor recording values near 0 Kgr/cm^2 as the engine was not operating. Moreover, some virtual sensors also reported values near 0. The messages reporting events were transmitted asynchronously to the recording mode so they took priority over the recorded data packets and arrived within seconds of their generation alerting the user of the change in operating condition promptly. The system performed unobstructed and the statistical performance of the network was requested at the end of the recording period through the designated remote command. The transmission attempts for each packet were logged on each Smart DAQ locally and were analysed at the end of the case study recording period. No other issues were recorded and no failures of the Smart DAQ system were observed in this period.
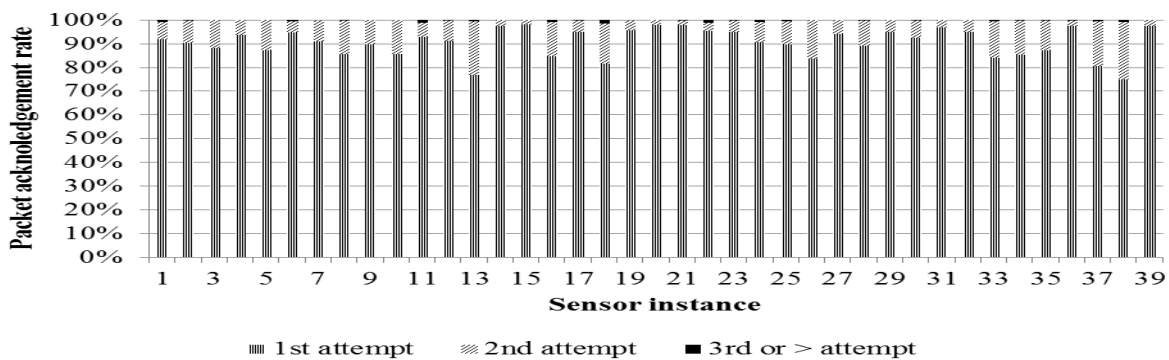

Fig.8: Packets successfully received for each sensor on 1st, 2nd or later transmission attempt.

Moreover, Figure 9 presents the network traffic load in Bytes per day over the duration of the experiment. The minimum possible if all packets were sent only once was recorded to be 5616 Bytes for the pre-processed data case while calculated at 43200 Bytes per day if data was to be sent directly in the raw format. This analysis includes the bytes used for the custom message protocol created for this system but does not include the information that is also appended to the messaged by the ZigBee protocol envelop.
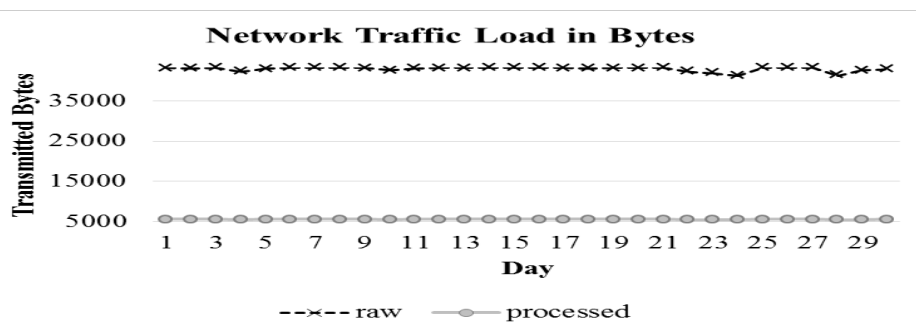

Fig.9: Number of bytes transmitted after pre-processing against raw data bytes throughout the month.

After the data was received at the receiver unit, each stream was post-processed independently and the data received for each time window were decomposed to a stream of data points to cover the full

length of the window. A 10 minute window was selected and each sensor was sampled for 1 second every minute at a 100 Ksps. The sleep mode was timed to 59 seconds. The post-processed signal was decomposed from the 10 minute statistical information to 10 readings covering minute intervals. This generated set was compared to the original data for each of the sensors. Figure 10 presents an example of the correlation of the two sets for sensor instance 1 (Fig. 10a) and sensor instance 39 (Fig. 10b). Table II presents the R2 value as a result of the correlation analysis between the two sets for each of the sensor instances.

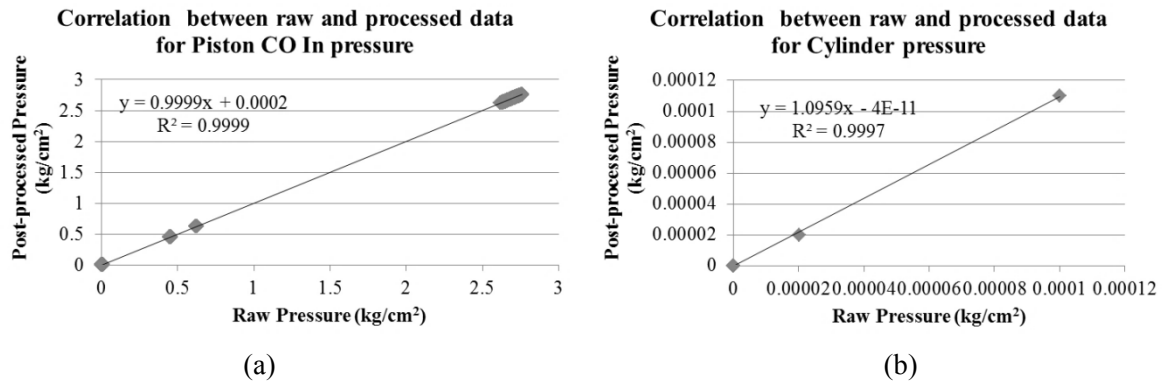(a)   (b)

Fig.10: Example of correlation analysis between initial data and post-process generated data for two cases (a) the virtual sensor (No. 11) (b) the physical sensor (No. 39).

As demonstrated from the results the changes that occur in the dataset are picked up by the process and no information is lost in any of the sensors either virtual or physical that were included in this case study. Thus, it is demonstrated that reduction of the transmitted information does not result in any loss of information particularly when events can be captured and incorporated in the result. The proposed methodology can thus provide an alternative to sensor networks that suffer from significant interference such as those deployed onboard ships.

Table II: Results of correlation analysis in terms of R^2 values for each sensor instance

No.	Measurement	R^2	No.	Measurement	R^2
1	Thrust Bearing LO Outlet Temp	1	20	IntShaft 1 Bearing Temp	1
2	TCLO 1 Input Press	0.999	21	IntShaft 2 Bearing Temp	1
3	TCLO 1 Input Temp	1	22	IntShaft 3 Bearing Temp	1
4	TCLO 1 Output Temp	1	23	Main Lube Oil Input Pressure	0.999
5	TCLO 2 Input Press	0.999	24	Main Lube Oil Input Temperature	0.999
6	TCLO 2 Input Temp	1	25	Cylinder Input JCFW Pressure	0.998
7	TCLO 2 Output Temp	1	26	Cylinder 1 Output Exh Gas Temp	1
8	Scav Air Manifold Press	1	27	Cylinder 2 Output Exh Gas Temp	1
9	Scav Air Rec 1 Temp	1	28	Cylinder 3 Output Exh Gas Temp	1
10	Main Engine Start Air Press	0.999	29	Cylinder 4 Output Exh Gas Temp	1
11	Piston CO Input Press	1	30	Cylinder 5 Output Exh Gas Temp	1
12	JCFW 1 Output Temp	0.999	31	Cylinder 6 Output Exh Gas Temp	1
13	JCFW 2 Output Temp	0.999	32	Cylinder 7 Output Exh Gas Temp	1
14	JCFW 3 Output Temp	1	33	Cylinder 8 Output Exh Gas Temp	1
15	JCFW 4 Output Temp	1	34	Aft Camshaft Bearing Temp	0.999
16	JCFW 5 Output Temp	0.999	35	Fore Cam Bearing Temp	0.999
17	JCFW 6 Output Temp	1	36	Exh Gas Out After Turbo Charger 1 Temp	1
18	JCFW 7 Output Temp	1	37	Ex Gas Out After Turbo Charger 2 Temp	1
19	JCFW 8 Output Temp	1	38	Main Engine Control Air Input Press	0.999
			39	Cylinder 1 pressure	0.999

From the results reported in Table II the only sensor that reports a R^2 of 0.998 was the Cylinder Input JCFW Pressure (No 25). Figure 11 below presents the raw recorded pressures and the processed/generated pressures against time in (a) and as a scatter plot in (b). As demonstrated even in this representative as worst case result, no information loss is recorded.

<div align="center">(a)</div>

Crellation between raw and processed data

$$y = 0.9999x + 0.0003$$
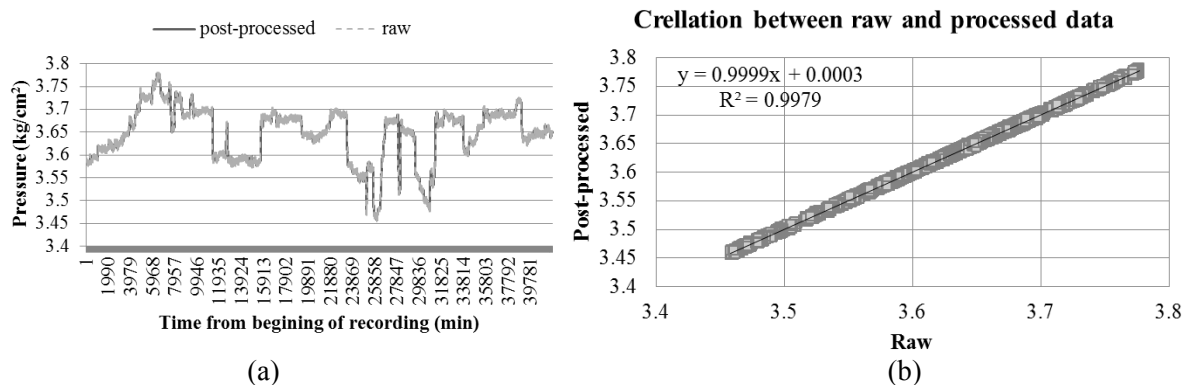$$R^2 = 0.9979$$

<div align="center">(b)</div>

Fig.11: Worst case result of correlation analysis between initial data and post-process generated data
(a) the two sets presented against the time for the duration of the case study (b) correlation analysis.

The two sets were then further processed through the reliability analysis tool and DSS. These results are not presented in this work due to practical limitations. However, as the data sets used for the virtual sensors were collected from a ship that is at optimum condition the DSS did not suggest any actions as no failures or warnings were detected. In that respect, the presented DSS algorithm was able to detect that no action needs to be suggested for all 39 instances. This includes the case were the physical sensor was recording near 0 values. If the event was not generated to warn the DSS that this equipment is not operating a failure would have been identified. Thus the incorporation of events provides benefits not only to data management so that the processed data correlated well with the raw but also to the analysis and decision suggestion parts of the system.

The following section will present a description of related work and highlight the differences with the novel approach proposed in this paper.

7. Related Work

In the last few years wireless sensor network systems have started emerging providing solutions for condition monitoring in the shipping industry. Two commercial systems are LAROS and KONGSBERG's wireless CBM system while no reference of academic approaches is made in the literature to the best of the authors' knowledge, LAROS (2015), Katsikas et al. (2014), Katsikas (2013), KONGSBERG (2017). These systems are both based on industrial wireless communication protocols but are utilising an embedded system approach with minimal processing at the edge of the network. In contrast to the work presented in this paper that method creates a significantly higher cross-talk noise and interference within the particular environment of the engine room. Moreover, these systems do not utilise an event recognising and response approach. Finally, the referenced Kongsberg system is only operating wirelessly in very short distances and a cable from the antenna to the collection point needs to be installed. In that respect, this system addresses an entirely different issue which is the access and ease of installation of the sensors in specific locations. This view is out of the scope of the proposed system presented in this paper.

Another area of related work is the use of industrial wireless protocols for data transmission onboard ships. In this area the amount of published work is also restricted compared to existing work in other industrial applications. A few publications support the use of industrial wireless protocols and demonstrate that it is possible to deploy such networks for condition monitoring, Koutsoubelias et al.

(2016), Katsikas et al. (2014), Katsikas (2013). Thus, this work further strengthens the viability of the proposed approach. Furthermore, Paik et al. in (2009) and (2007) present measurements on the utilisation of industrial WSNs in a full ship installation not only within the engine room but also across decks to other areas of the ship. Thus, not only it is possible to establish reliable communication but by employing delay tolerant networking as proposed in this paper and an event based alert system it is even possible to establish highly reliable data transmission suitable for industrial applications. Finally, WSNs have also been used by White et al. (2010) in tracking the location of containers onboard a container ship. Once again this is another example of the reliability and viability of such networks in ship applications.

Another area adjacent to the proposed approach is the development of purpose build break-out boards or capes for commodity hardware. Signal acquisition for industrial purposes has traditionally been one of the most expensive areas of embedded systems development. In recent years with the rise of commodity hardware such as the Raspberry Pi, Beaglebone and Arduino there has been an urge to provide speciality break-out boards and component based hardware developments such as capes for the BBB which are purpose build but allow ease of integration, Lewis (2015), Molloy (2015). This trend had recently reach the signal acquisition world and a cape for BBB named PRUDAQ was presented in August 2016 supported by Google Research, GroupGets (2016). This card does not support high voltage industrial sensors as the one proposed in this paper. However, it further strengthens the argument that such systems are required by both industry and academia in order to support the IoT generation of systems, Weisman (2016).

Decision support systems have enjoyed varied attention in several industries of the past few decades. It has been identified that DSS systems cannot be generic for all industries and all applications, Makowski, (2011), Vallerio et al., (2015). Hence, publications in the condition monitoring of ship applications have been reviewed. Jardine et al. (1997) presents one approach using hazard modelling which takes into account cost and age models along with a system based on maximum likelihood estimations advising strictly on replacement of parts. A control theory based approach is also presented by Christer et al., (1997) again to identify the time for replacement of parts. Khac Tuan et al. (2014) present a more sophisticated system that is based on degradation, threshold and failure mode integration. However, the interaction between failure modes and components of a system is not considered. A reliability analysis technique is presented by Dikis et al. (2016) and Lazakis et al. (2016, 2017) which considers these interactions but does not include vibration measurements. However, none of the above consider constrains such as availability of parts, crew expertise and weather conditions which may affect the decisions to be made as well as parameters such as performance and energy efficiency. Such a DSS is not previously published in literature to the best of the authors' knowledge. This work proposes a DSS which is a multiple parameter multiple constrain optimisation problem and allows for user defined constrains to be added to the system.

8. Conclusion

In conclusion, through the proposed methodology some of the inhibitors in acceptance of this technology are addressed such as increased security of data, ensuring data ownership and providing clear benefit to both the engineers onboard the vessel and management through the DSS software. Furthermore, the performance of the wireless network is demonstrating that the proposed system supports highly reliable data transfer. Additionally, through the proposed system the particular noise and interference conditions in the ship engine room are addressed without compromising data integrity, data quality, security and safety onboard the vessel. The results demonstrate correlation between the data recorded onboard a ship in voyage and the data that have been processed through the proposed approach. As such, this novel system can be utilised in real industrial applications to support any post-processing methodology while ensuring data integrity and security.

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