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Article

Utilizing the Evidential Reasoning approach to determine a suitable wireless sensor network orientation for asset integrity monitoring of an offshore gas turbine driven generator

Sean Loughney[a*], Jin Wang[a], Dante B. Matellini[a], Trung Thanh Nguyen[a]

[a] *School of Engineering, Faculty of Engineering and Technology, Liverpool John Moores University, Byrom Street, Liverpool, L3 3AF, UK*

* *Corresponding Author: S.Loughney@ljmu.ac.uk*

Co-Authors email:

J.Wang@ljmu.ac.uk

D.B.Matellini@ljmu.ac.uk

T.T.Nguyen@ljmu.ac.uk

ABSTRACT: This research proposes the most ideal Wireless Sensor Network (WSN) topology for remote integrity monitoring of an offshore gas turbine driven generator. The intention is to design the structure of a number of WSNs within the electrical generation system with varying connection types and methods of relaying data. The research is concerned only with the design of the WSNs, *i.e.* the hardware and orientation of the sensor nodes and not the software, programming or data protection. This will potentially provide a good base, once an ideal WSN design is determined, to expand the network further incorporating more criteria and develop the necessary software to complete the WSN. The work applies the Evidential Reasoning approach to a number of WSN topologies in order to determine the most suitable based upon an outlined set of performance criteria. Axiom based validation of the methodology is also provided within the analysis.

1 INTRODUCTION

This research focuses on the development of a Wireless Sensor Network (WSN) for asset integrity monitoring for a safety critical offshore system. The system in question is the electrical generation system on board a fixed steel platform in the North Sea. The intention is to design the topology of a number of WSNs within the electrical generation system with varying connection types and methods of relaying data. The research is concerned only with the design and topology of the WSNs. This should provide a good base to expand the network further incorporating more nodes and develop the necessary software to complete the WSN.

The purpose of this research is to begin the development of a WSN that would be able to monitor, detect and send information regarding the asset integrity of an offshore system. It has been found in previous research, (HSE, 2014) (Loughney, et al., 2017) (Loughney & Wang, 2017), that there are cases where the full extent of an incident is not reported, such as a fuel gas release. For example, from 1992 to 2014, 40% of fuel gas and power turbine gas releases were not detected by an automatic sensor but were detected by human detection. The human detection includes smell, visual and a portable detector. In the instances of human detection, the recording of information is scarce, with 56% of fuel gas release incidents having little to no information regarding the location and cause of the release and in some cases, the extent of the dispersion. Furthermore, the majority of the 56% of releases with incomplete information and data were regarded as “Significant”, in terms of their severity level (HSE, 2014). A system must be developed to detect these failures and releases given that there is no human presence on board (Loughney, et al., 2017) (Loughney & Wang, 2017) (Zio, 2018). This moves the research into the Internet of Things (IoT) and WSNs. The novelty of this research is not only in the development of a system that can monitor asset integrity for preventative or predictive maintenance, but also in the application of a Multiple Criteria Decision Analysis (MCDA) methodology in order to determine the most sufficient WSN topology to achieve this monitoring.

In the current world smart homes, smart water networks, intelligent transportation networks, *etc.* are infrastructure systems that connect the world together more than was thought possible. This common vision of interrelating systems is associated with a common concept, the IoT, where, through the use of sensors, an entire physical infrastructure is paired with information and communication technology. Intelligent monitoring and management can be achieved through the application of network embedded devices. In these sophisticated and dynamic systems, devices are interconnected to transmit useful information regarding measurements and control instructions through distributed sensor networks (Zio, 2018) (IEC, 2014) (Chong & Kumar, 2003). Furthermore, A WSN is a network formed by several sensor nodes, where each node is equipped with a sensor to detect physical phenomena such as: heat, light, sound, pressure, *etc.* WSNs are considered a revolutionary information harvesting method in the building of information and communication systems which will greatly improve the systems efficiency and reliability. WSNs feature easy deployment and vast flexibility of devices, and with the rapid growth in today’s development of sensor technology, WSNs are becoming the key technology for IoT (IEC, 2014) (Fischione, 2014) (Harrop & Raghu, 2018).

There is increased demand for diverse applications within the communication services industry, within which WSNs gain increasingly more attention. WSN development and deployment has been and is continually being enhanced in terms of autonomously supporting a variety of potential applications as well as providing more adept solutions. However, decisions lie within the appropriate selection of key WSN features such as topology, the number of sensors, and the most efficient pathway for data transfer. This has given rise to the application of MCDA techniques to determine the best or most suitable aspects of WSNs for specific deployment scenarios. One such example is the work presented by Tang, et al., (2014) in which an algorithm is developed based upon multiple criteria decisions making to determine the most energy efficient routing within a WSN. Their research considers key factors affecting the network lifetime, and a chaos genetic algorithm to determine the next most energy efficient hop in the data route (Tang, et al., 2015) (Jia, et al., 2020). Similarly, a fuzzy decision model has been applied to the selection of wireless technology by Jiang, et al., (2012). This work develops an evaluation hierarchy with six major criteria and a set of sub-criteria in order to determine the most suitable WSN technology for the tracking of construction materials. The work concluded that a Wi-Fi device was the best alternative, as opposed to RFID, GPS, ZigBee and UWD devices (Jiang, et al., 2012). Finally, Gao, et al., (2010) propose a novel MCDA approach to cluster head selection within WSNs. The approach combines fuzzy-AHP and hierarchical fuzzy integral in order to analyse the optimum criteria that can influence energy efficiency to determine the selection of cluster head nodes in the WSN (Gao, et al., 2010).

This paper produces a brief literature review providing background into the research (Section 2), develops a number of WSN options related to the outlined problem and outlines a decision-making methodology (Section 3), demonstrates the use of the outlined decision-making methodology and presents decision making results through a case study (Section 4), and finally presents a brief conclusion (Section 5).

2 BACKGROUND

The initial development of WSNs was motivated by military applications, such as surveillance in conflict zones. In the modern world, they consist of independent devices using sensors to monitor physical conditions with applications across industrial infrastructure, automation, health and consumer areas. These sensor devices are usually spread over areas of varying size. The sensor nodes are usually transceivers scattered within the sensor field where they can detect and transfer information to the gateway or sinkhole for use by the end user (IEC, 2014) (Fischione, 2014).

Recent advancements in the fields of communication and micro-electromechanical technology have resulted in a significant movement in WSN research. The increasing research of WSNs has put its focus in networked information processing and networking technology for application in highly dynamic environments. Similarly, sensor nodes have become increasingly smaller in size with greater output potential and a reduction in cost, hence many applications in the civilian world have emerged, such as: vehicle sensor networks, environment monitoring and body sensor networks. Currently WSNs are viewed as the most important technologies of the 21st Century, with countries like China incorporating WSNs in their national strategic programmes (Ni, 2008).

This has resulted in a massive acceleration in the commercialisation of WSNs and many more technology companies are emerging (IEC, 2014).

Industrial automation is one of the key areas of WSN applications. The Freedonia Group state that the global market share of sensors for industrial use is approximately $11 billion USD, and with the cost of installation, including cabling costs *etc.*, the usage is up to $100 billion USD. It is this cost that hinders the further development of industrial communication technology. WSNs can improve the whole industrial process by securing the important parameters that are unavailable through online monitoring due to the costs stated by the Freedonia Group (IEC, 2014).

It has been estimated that 39% of the sensors introduced between 2011 and 2016 have been applied to new, innovative applications which have only been made possible by the development of WSNs. IDTechEx research has found that the WSN market will grow to $1.8 billion by 2024. These figures refer to WSN defined as wireless mesh networks, i.e. self-healing and self-organising (IEC, 2014) (Fischione, 2014) (Harrop & Raghu, 2018).

75% of industrial WSN income arises from the process industry, with Oil and Gas being the fastest growing sectors. For example, PetroChina is conducting IoT projects across its oil fields, with the focus on the reconstruction of more than 200,000 oil wells. The WSN technology applied in the oil wells will provide the ability to monitor the oil well production and the integrity of the oil well systems to ensure safe production (Halter, et al., 2012) (IEC, 2014) (Harrop & Raghu, 2018) (Raza, et al., 2017).

Generally, a WSN consists of a number of sensor nodes and a gateway for connection to the internet. The general deployment of WSNs follows a number of steps and is shown by Figure 1. Firstly, the sensor nodes will broadcast their status to the surrounding environment as well as receiving information regarding the status of other nodes in the sensor radius. Secondly, the nodes are organised into a connected network dependant on the given topology (single-hop, multi-hop). The final stage is determining the most efficient routes for the information to be transmitted through (IEC, 2014) (Mhatre & Rosenberg, 2004).

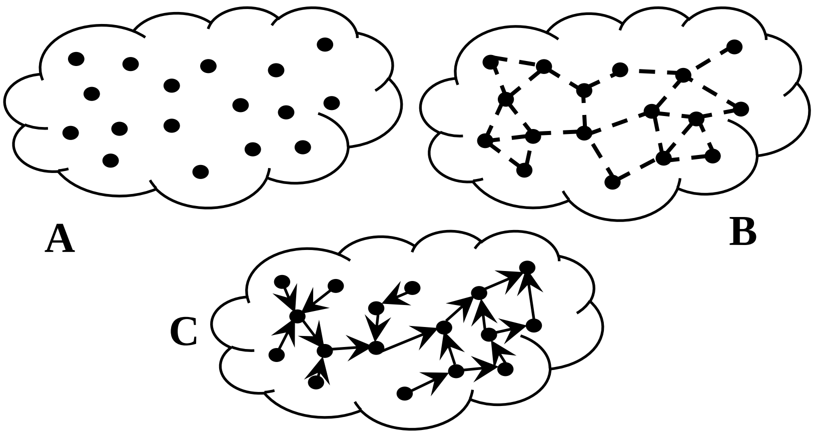

Figure 1: Organisation and Transmission process of a WSN. A) Waking and Detecting, B) Connecting as a network & C) Routing through multi-hop topology (assuming data routing from left to right)

2.1 Single-hop Transmission

When the transmission ranges of the sensor nodes are large enough or the radius of the sensor cloud is less than that of the transmission radius of the sensor nodes, the nodes can transmit their information directly to the centralised gateway. They form what is known as a star topology with single-hop communications, as shown by Figure 2. When sensors utilise single-hop communication, there is no relaying of packets of information. Since the communication is directly between the sensor node and the gateway, each node should transmit their data in sequence, *i.e.* one at a time. In this instance, the lifetime of the network is determined by the node with the shortest life span. In a single-hop network, this is the node furthest away from the gateway as it must expend the most energy to transmit information (Gupta & Kumar, 1998) (Chhaya, et al., 2017) (Raza, et al., 2017).

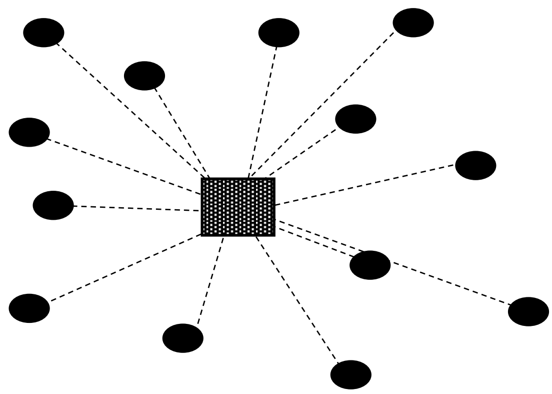

Figure 2: Star topology with single-hop communication from sensors to a central gateway

2.2 Multi-hop Transmission

It is more common for the transmission ranges of the sensor nodes to be less than the radius of the sensor cloud, in which case the transmission range of the sensor nodes is kept at a minimum to conserve battery life. In this instance, nodes relay information from one another, utilising the shortest possible route to the gateway. Here the nodes form a mesh topology using multi-hop communications. In this topology not only do nodes have to capture and process their own data, but they must collaborate to propagate sensor data towards the gateway (Fischione, 2014) (Raza, et al., 2017). Figure 3 shows an example of multi-hop routing. When a node serves as a relay for multiple routes, it has the opportunity to analyse and pre-process data in the network, which can lead to the elimination of redundant information or aggregation of data that can be smaller than the original data set. Furthermore, when considering multi-hop communication, each sensor has a communication range *R*, as shown in Figure 3, and *R* must be sufficiently large to maintain connectivity across the network. Gupta & Kumar (1998) developed a lower bound on the communication radius, *R*, in order to ensure connectivity of the nodes with a high probability when *n* nodes are distributed uniformly or randomly. This development is still highly relevant in research today.

2.3 WSNs in Offshore Industry

The requirement to collect measurements relating to temperature, flow, pressure and vibration, in often remote and unsafe locations is common and vital in the offshore oil and gas industry. The offshore industry is continually expanding and progressing, particularly technological advances. This growth in industry and technology is also driving the need to measure, record and transmit data in real time. Wireless sensor networking is the way to do this without the need for cables and the associated problems that come with unsafe and inaccessible locations (Akhondi, et al., 2010).

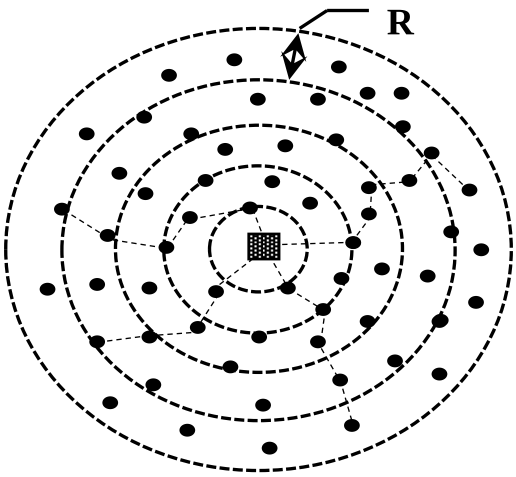

Figure 3: Multi-hop wireless network with indicated sensor communication radii, R

Offshore platforms house an abundance of remote and unsafe locations associated with a variety of systems. Wired sensors and equipment require power, cables and conduit to reach devices in remote locations. This is costly, inconvenient, time consuming and in some cases impossible. Other factors include the manpower associated with the installation, as well as the monitoring recording and data processing. This leave a lot of room for human error, which is a big concern when operating in high risk and extreme offshore conditions. (Lajoie, 2010)

WSNs can eliminate the expensive and inconvenient conduit and cables of wired networks. Measurement data can be collected accurately and in real time for faster response and decision making, with limited loss in the system integrity and availability. Similarly, a WSN can minimalize the personal required to perform manual duties where there is a high-risk level (Lajoie, 2010).

The offshore industry includes processes for exploration, extraction, refining, transporting, and marketing of products. As the demand for fossil fuels increases, so does the need for offshore companies to develop and employ new technologies. There is also a need to improve operations in order to increase productivity, reduce injury and fatality and maintain system integrity. WSNs can quickly be organised and continually adapted to monitor and control a surrounding environmental conditions and machinery.

As wireless technologies are being developed, there is an increase in the use of wireless sensors being deployed on older, end of life platforms in order to gain new insights and to attempt to optimise the platforms production (Carlsen, et al., 2008). However, there are many challenges associated with the deployment of WSNs on offshore platforms (Akhondi, et al., 2010). Studies have shown that required changes in plant work processes may be the largest hindrance on the introduction of WSNs into the oil and gas industry. It was noted by Petersen, *et al.* (2008) that problems are typically experienced when human factors are ignored in the adoption of new technology.

WSNs are a key investment across the whole offshore oil and gas industry, including pipelines, exploration, production and transportation. By providing secure and reliable wireless communications, WSNs enable automation and control solutions that are not feasible with wired networks. It is a multidisciplinary research area which requires good collaboration between users, hardware designers and engineers and software developers (Akhondi, et al., 2010) (Kumar & Chaurasiya, 2018). There are four main application areas where WSNs would be extremely useful on-board offshore platforms:

Remote monitoring: WSN solutions provide remote monitoring capabilities or the offshore industry to adhere to new technology, regulatory and productivity demands. Examples of where WSNs can be applied for remote monitoring purposes include (Petersen, et al., 2008) (Coutinho, et al., 2018):

- Pipeline integrity monitoring.
- On-board system integrity monitoring.
- Tank level monitoring.
- Wellhead automation and monitoring.

Condition monitoring and maintenance: The overall aim of fault diagnostics is the estimation of the status of a component through sensor measurements and the monitoring of system components. Equipment diagnostics tries to determine the root cause of a component failure whereas system diagnostics is performed on a system of components. Utilising sensor measurements preventative and almost predictive maintenance can be performed, and subsequently post-fault diagnostics is improved. The predictive maintenance methodologies require that the system be monitored in real time. Sensors may detect vibration, temperature, power consumption, gases, performance and electromagnetic properties. When combined with other sensors in a network, these continuous signals can demonstrate clear and significant information about the status and integrity of a component or system. This allows for the detection, or even prediction, of potential upcoming failures (Ferreira & Alves da Silva, 2007) (Coutinho, et al., 2018).

Toxic substance monitoring: During the exploration and extraction of oil and gas, many types of toxic gases are produced as a product or by-product of the production processes. The largest concern, with all toxic substances, is the potential for leaks. Not only is this damaging to people and the environment, but also any leak in a transport pipeline requires a shutdown of the process. Leakages can be caused by any number of faults, such as: corrosion, earthquakes, general wear and tear, material flaws and even sabotage (Akhondi, et al., 2010) (Xiaojuan, et al., 2009).

Due to the extensive installation and maintenance costs, a stationary, wired sensing system may not cover the whole containment and transport system. Hence, each crew member must carry a portable sensor device as a safety precaution. The application of a WSN here would potentially give a cross section of any leaks for a more extensive analysis. Existing sensing systems do not correlate data, sensors produce information independently, and so determining the nature of the leak can be difficult and time-consuming (Xiaojuan, et al., 2009).

Production performance: Given the relevant level and amount of data, from a number of performance aspects of an offshore platform facilitated by WSNs, an unsupervised self-organising map can prioritise key sensor values and classify operational performance. This can show when a plant is operating normally or abnormally. This type of WSN is often used in conjunction with supervised methods. Whereby the unsupervised network will perform pre-processing of data and the supervised system will conduct the analysis and estimate the associated parameters (Akhondi, et al., 2010).

2.4 Sensor Placement and WSN Orientation

2.4.1 WSN Design Outline

The problem considers a region of an offshore platform to be covered by wireless sensor nodes. The number of sensors is determined by the requirements of the application. Typically, each sensor node has a sensing radius and it is required that the sensor provides coverage of the specified region with a high probability. The sensing and transmitting radius of the node depends on the phenomenon that is being sensed as well as the sensing hardware of the node. Hence, in general, the number of sensor nodes is dictated by the application. In this research, the application is known and so the problem of where to deploy the sensor nodes is an easy one to solve. The application here is the integrity of the electrical generation equipment on board an offshore platform, more specifically the Thistle Alpha Platform located in the North Sea. The WSNs to be proposed will focus on the key areas where integrity of the electrical generation equipment must be maintained. These key areas are outlined as Gas Turbine Sensing and Monitoring (Meggitt, 2016) (Raza, et al., 2017).

In order to first develop the WSNs topology, one must know the domain in which the sensors will be deployed. In this problem, the sensors will be distributed within the electrical generators located within the electrical generation module of the Thistle Alpha platform. There are a number of steps involved in the generation of the domain (Prauzek, et al., 2018) (Sarobin, 2020) (Haque & Baroundi, 2021)

1. Domain – The domain must first be established in order to definitively and accurately place the sensor nodes.
2. Dimensions – The dimensions of the domain must be specified in order to determine the size of the sensor field, as well as to determine the worst-case battery life and in the case of multi-hop connectivity, and to determine the average size of each nodes transmitting radius.
3. Sensor placement – Once the dimensions of the domain are known the sensor nodes can theoretically be placed to begin forming the network. The nodes are placed based upon the phenomenon that they are going to be detecting.
4. Data Transmission – Once the sensors nodes have been appropriately placed, a decision is made as to whether the network should be single-hop or multi-hop based upon a given set of criteria.

The WSN designs proposed in this research are only part of the initial stages of developing the Asset Integrity Case or NUI-Installations. The WSNs are not to be considered as complete models for real-time application at this moment in time (Haque & Baroundi, 2021).

2.4.2 Establishing the Domain

The domain has already been identified as the electrical generation module on the Thistle Alpha Platform. The Thistle Alpha Platform, located in the North Sea, has three gas turbine driven electrical generators, (termed Unit A, Unit B & Unit C), each of which is capable of providing 100% of the platform power requirements. The platform is currently part of the Thistle Late Life Extension (LLX) strategy, which aims to recover over 35 million barrels of oil through to 2025 from the Thistle and Deveron oil fields. In order for the platform to be operable to 2025 and beyond, the LLX strategy incorporates a series of major initiatives to improve structural and topside integrity, upgrade safety and control systems, improve the oil production and water treatment process and provide reliable power. This makes this platform a perfect candidate for the development of dynamic asset integrity monitoring. Figure 4 shows the generic outline of the main electrical generation module, which houses generator unit’s A and B (Cresswell, 2010).

While Figure 4 gives a good overview of the generic layout and location of equipment, it is not enough to accurately create a size model of the generator module (Module 2). However, it is possible to determine the dimensions of the module and the equipment from the plot plans of the Thistle Alpha Platform, which were accessible for this research. From these more detailed plans, the dimensions of module 2, the electrical generators and the orientation of equipment in the space can be determined. Table 1 gives an outline of the key dimensions, with all equipment dimensions (*i.e.,* turbine and alternator) defined as external measurements.

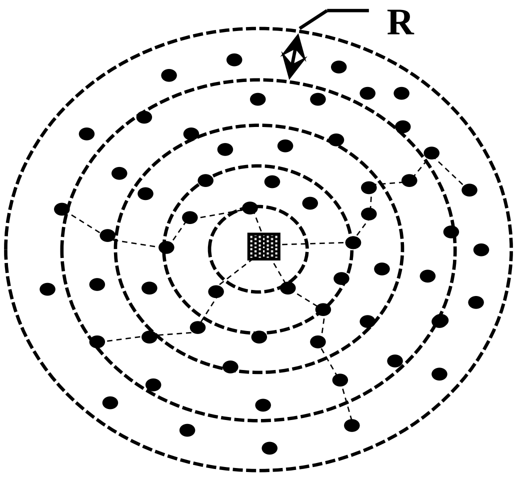

Figure 4: Multi-hop wireless network with indicated sensor communication radii, R

Table 1: Dimensions of module 2 and electrical generation equipment

Item	Measurement
Module Length	27m
Module Width	13.8m
Module Height	10m
Height to Mezzanine	6m
Total Generator Length	17m
Alternator Length	7.8m
Alternator Width	4.3m
Alternator Height	4.3m
Gas Turbine Length	9.2m
Gas Turbine Width	2.9m
Gas Turbine Height	3.5m
Spacing between Alternators	0.9m
Distance of Unit A from the Module Wall	1.4m

2.4.3 Sensor Placement

After the domain and dimensions have been identified, it is possible to place the sensor nodes and determine the size of the sensor field. The nodes are dependent entirely on what they are detecting and are placed accordingly. In this research the focus is on the integrity of the gas turbine generator therefore, a finite number of nodes are proposed to keep the complexity of the WSNs as low as possible (Kumar & Chaurasiya, 2018) (Prauzek, et al., 2018) (Peng, et al., 2018) (Haque & Baroundi, 2021).

It is necessary to identify where the sensor nodes should best be deployed in order to accurately maintain integrity. A key place to begin is to identify where gas turbines and alternators already have wired sensors in place to monitor the integrity of equipment. Meggitt Sensing Systems currently identifies a number of key areas where wired sensing and condition monitoring takes place within an electrical generation unit (Meggitt, 2016) (Raza, et al., 2017) (Peng, et al., 2018) (Sarobin, 2020). These are outlined as follows:

1. Absolute vibration – The sensors here determine the seismic vibration of the system relative to the Earth (Zargar, 2014) (Lu, et al., 2018) (Peng, et al., 2018).
2. Shaft vibration – These sensors monitor the levels of vibration incurred by the main generator shaft that runs through the gas turbine and the alternator. The sensor here provides data on the vibration of the shaft against the bearings (Zargar, 2014) (Lu, et al., 2018) (Peng, et al., 2018).
3. Shaft displacement – Sensors and probes here are used to measure the movement of the shaft in the vicinity of the probe. They cannot measure the bending of the shaft away from the probe. Displacement probes indicate problems such as unbalance, misalignment, and oil whirl (Zargar, 2014) (Lu, et al., 2018) (Peng, et al., 2018).
4. Static oil pressure – Sensors here measure the force per unit area exerted on the walls of a container by the stationary fluid. In this case the stationary fluid is the bearing oil (Kiameh, 2003) (Peng, et al., 2018).
5. Temperature – The sensors here simply measure he temperature of various areas of the generator such as: temperature of the combustion, the exhaust gases and the bearing lube oil (Kiameh, 2003) (Peng, et al., 2018).
6. Speed – This sensor measures the speed of the main shaft at the bearings in-between the gas turbine and the alternator. This node indicates whether the turbine is in danger of running overspeed or not at the required speed. Typically, the gas turbines on the Thistle Alpha platform run at 3,600 rpm (RMRI Plc., 2009) (Peng, et al., 2018).
7. Combustion pressure – The combustion section has the difficult task of controlling the burning of large amounts of fuel and air. It must release the heat in a manner that the air is expanded and accelerated to give a smooth stream of uniformly-heated gas at all starting and operating conditions. This must be accomplished with minimum pressure loss and maximum heat release. Therefore, monitoring the combustion pressure is vital for the operation of the turbine (Kiameh, 2003).
8. Blade Health – Heavy duty industrial gas turbines are widely used in power generation plants worldwide. Axial flow compressor and expansion turbine are key subsystems of the gas turbine. Due to inlet air flow aero dynamic load and rotor rotation, various mode displacement and vibration on the turbine blades are excited. Excessive vibration may accumulate high cycle fatigue and thermal mechanical stress on a rotor blade, and cracks may initiate and propagate over time. Having sensors here to detect

and monitor blade cracks and provide early warning before material liberation is the main focus for any blade health monitoring system (Yu & Shrivastava, 2016).

9. Emissions – The purpose of sensors here is to detect the quality of the exhaust emissions from the gas turbine. There are strict regulations in place that regulate the levels of NOx and CO_2 in turbine emissions. Most air pollution NOx measurements are done on a volumetric concentration basis, in parts per million by volume (ppmv) or in some cases in a weight/volume fraction such as mg/m^3. Uncontrolled gas turbine NOx emissions are in the 150–300 ppmv range (about 300–600 mg/m^3) (Klein, 2012).
10. Alternator discharge – Sensors here measure the level of partial electrical discharge from the alternator. Partial discharge is an electrical discharge that occurs across a localised area of the insulation between two conducting electrodes, without completely bridging the gap. It can be caused by discontinuities or imperfections in the insulation system. Discharge monitoring thus gives an indication of deterioration of the insulation and is an indicator of incipient faults (HVPD, 2016) (Peng, et al., 2018).

After these key areas have been identified and outlined, the locations of the sensors can be assigned. Figure 5 shows the prime locations for the wireless sensor nodes within the gas turbine and the alternator.

As shown in Figure 5, there are 31 proposed sensor nodes within each generator unit, hence the sensor field is comprised of 62 sensor nodes at this initial stage. Starting from the left of Figure 5, it can be seen that there are 3 nodes on the first bearing set, monitoring the absolute vibration, the static oil pressure and the temperature. This arrangement at the first bearing is coherent with Meggitt, (2016) application of probes and sensors at this position. Following this to the compressor turbine, there are 8 nodes monitoring the blade health, and 2 monitoring the power turbine. There are combustion pressure sensors monitoring the combustion chambers due to the small margins of pressure loss available.

Continuing through the generator to the exhaust of the power turbine and the bearings between the turbine and the alternator. There are 2 nodes monitoring the emissions of the turbine as well as 6 nodes on the bearing. There are more nodes here due to it being a midpoint location on the main shaft. Therefore, along with the absolute vibration, oil pressure and temperature sensors, there are also nodes monitoring the speed of the shaft at the exit of the power turbine, the relative vibration of the shaft to the middle bearing and the displacement of the shaft (Lu, et al., 2018). Monitoring the displacement and relative vibration of the shaft here are key as it is a potential vibration node point of the shaft, due to its locating from the two end bearings (Kiameh, 2003). Moving through the alternator, there are 4 nodes monitoring the partial discharge. Finally, there are 4 further nodes on the final bearing after the alternator. The nodes here again include absolute vibration, static pressure and temperature nodes, just as the first bearing. However, there is also a relative shaft vibration sensor due to there being an exciter after the alternator, which does not form part of the analysis but must still be treated as though it is there in relation to the operation of the generator (RMRI Plc., 2009) (Kiameh, 2003).

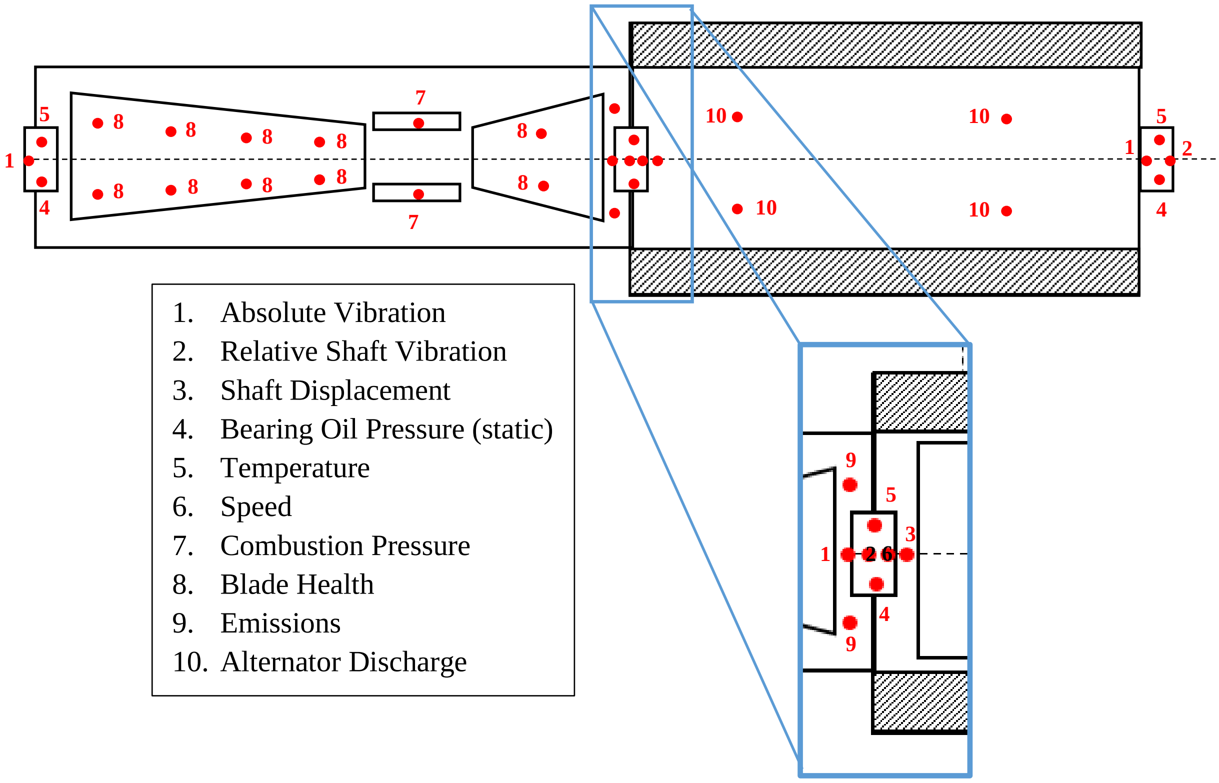

Figure 5: Proposed locations of the wireless sensor nodes within the electrical generator

2.4.4 Data Transmission

As a number of sensors, with a stated purpose, have been proposed, then it is possible to determine the method of data transmissions. There are two main data transmission types: single-hop and multi-hop, as outlined in Sections 2.1 and 2.2. However, it is possible to split these further. It is possible to have single-hop routing directly to the gateway node and single-hop transmission via cluster heads. Similarly, it is possible to have multi-hop connectivity based upon the size of each sensor's average radius of connectivity, *i.e.* multi-hop with a large individual sensor radius (*R*), and multi-hop with a small individual sensor radius (Kumar & Chaurasiya, 2018) (Prauzek, et al., 2018) (Anand & Pandey, 2020) (Sarobin, 2020).

In this research and analysis four types of data transmission are to be analysed and compared against a set of criteria to determine the most applicable for use in integrity monitoring in an offshore environment. It is important to note that the gateway node is assumed to be on the top of the offshore module and any cluster head nodes are assumed to be on the mezzanine deck in Module 2, shown in Figure 4. These four forms of transmission are outlined as follows:

A. **Single-hop** - Nodes connect directly to the Gateway node. Due to congestion, Nodes transmit data in sequence. *i.e.* Node 1 transmits data, Node 2 cannot transmit until the gateway has received information from Node 1, and so on. Complexity is not applicable to the Single-hop design as all nodes send data to the same destination and do not relay data, as shown in Section 2.1 (Prauzek, et al., 2018).

B. **Single-hop with Cluster nodes -** Nodes transmit data to the nearest cluster node in sequence. Hence, several nodes can transmit simultaneously to different cluster nodes. Theoretically this requires less battery power than Single-hop as there are two short connections from the node to the cluster and from the cluster to the gateway, as opposed to one connection over a longer distance (Haque & Baroundi, 2021) (Prauzek, et al., 2018) (Anand & Pandey, 2020).

C. **Multi-hop with a smallest sensor node radius -** Nodes relay (transmit/ receive) information from each other to achieve the best route from the source node to the cluster node. The small radius denotes the smallest transmittable distance of the node. *i.e.* it would require more connections to reach the cluster node. Theoretically this requires more battery than Single-hop as the nodes must transmit and receive data (Kumar & Chaurasiya, 2018) (Anand & Pandey, 2020) (Haque & Baroundi, 2021).

D. **Multi-hop with a larger sensor node radius -** The theory is the same for the Multi-hop (Small *R)*, however, nodes have a larger sensor radius and can transmit/receive data from nodes further away, meaning fewer connections to the cluster node. This requires an increase in battery power to transmit/receive over a large area. Due to the large area, the network can almost act as a single-hop cluster network (Kumar & Chaurasiya, 2018) (Haque & Baroundi, 2021) (Prauzek, et al., 2018).

2.5 Evidential Reasoning approach

Numerous decision-making problems in management and engineering involve several criteria of both a qualitative and quantitative nature. It is the normal handling of qualitative criteria along with uncertain or incomplete information that causes complexity in multiple criteria assessments. There has been an increase in the development of theoretically sound methods and tools which deal with MCDA problems in a coherent, rational, reliable and repeatable manner (Yang, 2001) (Yang & Xu, 2002) (Chen, et al., 2013) (Chhaya, et al., 2017) (Zhang, et al., 2019).

There has been considerable research conducted on integrating techniques from Artificial Intelligence to Operational Research for handling uncertain information. From this line of research, the Evidential Reasoning (ER) approach was developed for MCDA. This method of decision-making is based on an evaluation analysis model and the Dempster-Schafer (D-S) theory of evidence. In more recent times, the ER approach has been applied to decision-making problems in engineering, design and safety and risk assessment and supplier assessment. For example, motorcycle assessment, cargo ship design (Yang & Xu, 2002) and marine system safety analysis (Ren, et al., 2005). The key component of the ER approach is an ER algorithm developed around a multi- criteria evaluation framework or hierarchy and the evidence combination rule of D-S theory (Yang & Xu, 2002) (Chen, et al., 2013) (Chen, et al., 2018) (Jia, et al., 2020) (Du & Zhong, 2021).

This ER algorithm can be used to aggregate criteria in a multilevel structure, and a rational aggregation process needs to satisfy certain self-evident rules, commonly referred to as synthesis axioms. Suppose there are two levels of criteria with general criteria at the top and several basic criteria at the bottom level. Each basic criterion can be assessed against a given set of evaluation grades. A criterion may be assessed against an individual or a subset of the evaluation grades, with different degrees of belief (Yang & Xu, 2002) (Chen, et al., 2013) (Fu, et al., 2019) (Du & Zhong, 2021).

3 METHODOLOGY

When developing a decision-making methodology it is important to clearly define the domain that it is to represent. The criteria must be appropriately allocated, with careful attention being paid to what each criterion shall represent and where they shall rank in the evaluation hierarchy. The fundamental part of developing a coherent decision-making method, with the ability to deliver coherent results, lies in its evaluation hierarchy and the allocation the belief degrees and weights. With this in mind, a decision-making method has been established to ascertain the most suitable WSN design for use in the asset integrity monitoring of an offshore electrical generation system. To ensure that a coherent method was established, knowledge was obtained through reviewing literature and conversing with industrial experts.

There are a number of steps involved in the procedure for applying a decision-making algorithm to a problem. Having a number of steps is key for maintaining consistency throughout the process and offers and element of confidence to the final analysis. There are key elements that the procedure must follow, these are outlined as follows.

3.1 Establish the domain and definition.

This involves putting boundaries in place in order to prevent the process from becoming too complex. It has already been stated in Section 2 that the WSNs shall be incorporated into the electrical generation system and a finite number of wireless sensor nodes have been established in key areas of the machinery.

3.2 Identify the objective.

This involves stating what results are to be expected to be achieved from the problem-solving process. For this procedure and analysis, the goal is to determine the most suitable WSN based upon a set of criteria related to the design of a WSN. Furthermore, the evidential reasoning approach is utilised for the decision-making process.

The first 2 steps of the decision-making methodology have been followed and identified by Section 2.4.

3.3 Identify a set of criteria relative to the problem.

This involves filtering possible criteria that are relative to the description and the objective. For this problem, the criteria were devised from literature studies based upon the key hardware criteria and criteria of a WSN. It is necessary to keep the criteria to a sensible number at this stage to avoid over complications when applying the decision-making algorithm.

In order to apply the ER algorithm to the decision of the most suitable WSN design for use in an offshore system, a set of variables and a hierarchical structure of general and basic criteria must first be defined. The variables and hierarchical structure are based upon the hardware requirements for a WSN and for application on an offshore platform. In this analysis, there are three general criteria outlined and eight basic criteria.

The criteria have been outlined based upon the requirement of WSN hardware in relevant literature studies (IEC, 2014) (Harrop & Raghu, 2018) (Chhaya, et al., 2017) (Akhondi, et al., 2010) (Carlsen, et al., 2008) (Chandrasekaran, et al., 2016). These general criteria are outlined as follows:

- *Complexity (x)* is defined as the intricacy of the WSN. Usually, this would be the number of nodes and their location, however, this is already bounded by the scenario on board an offshore platform. Hence, the complexity is defined by three basic criteria relating to the design and hardware:
    - *Transmission over the shortest possible route (e_1)*: The ability of the network to transmit information over the shortest possible route from one sensor node to the Gateway node.
    - *Transmission over the longest possible route (e_2)*: The ability of the network to relay information over the longest possible distance to the Gateway given that one or more nodes fail to transmit/receive data.
    - *Large number of cluster head nodes (e_3)*: The necessity of the network to have many cluster nodes in order to reliably transmit data to the Gateway.
- *Resilience (y)* is defined as the WSNs ability to deal with faults to the system. As this research does not include any software analysis, the issue of cyber-attacks cannot be fully analysed therefore, the resilience of the WSNs is determined by two basic criteria.
    - *Battery power (e_4)*: This has already been outlined in some detail, and in this analysis, it is defined as: The ability of the network to have a substantial source of battery power for the longevity of the network life and reduced time between maintenance. Battery power must be sufficient to power the sensors, initially, for several months.
    - *Relaying data (e_5)*: This is a key criterion as it deals with the ability of the network to relay information between nodes in the event of sensor node failures and/or network disruptions.
- *Maintainability (z)* focuses on the capability of the WSN design to be easy to maintain, its self-sustainability and the costs incurred by installation and maintenance. It is outlined by three basic criteria:
    - *Ease of Maintenance (e_6)*: This is dependent on the Complexity of the nodes, *i.e.* the number of components within the nodes (sensor, transmitter, receiver, battery size). Location is not a factor as all nodes in this study are located within the electrical power generator.
    - *Auto-Configuration (e_7)*: The ability of the network to auto configure on start-up and after maintenance. Nodes that can relay information can ease this issue, however, it is easier to program networks to auto-configure with less complex and fewer connections.

- *Cost (e_8)*: The cost of the network is determined by the number of nodes required (including cluster nodes), the sophistication of the nodes (battery size, transmitters, receivers and sensors) and the cost of maintenance.

3.4 Develop the evaluation hierarchy.

Once the criteria have been established, a hierarchy must be determined in order to coherently develop a solution to the problem. This hierarchy groups certain criteria under one general criterion. This allows for a smaller number of criteria to be aggregated gradually to reduce the calculation complexity of the decision-making algorithm (Yang, 2001) (Yang & Xu, 2002) (Wang, et al., 1995) (Sadeghi, et al., 2018).

The hierarchical structure is demonstrated by Figure 6. It can be seen from Figure 6 that WSN 1 (Single-Hop) is not associated with the first two general criteria *Complexity* and *Resilience*. This is due to a number of reasons; firstly, as the network is single-hop, the issue of transmitting over the shortest or longest route is not applicable. As previously outlined, the single-hop transmission has each node transmit their data one after another in sequence, directly to the gateway. Hence there is only one possible transmission route that each node can transmit data. Secondly, there are not any cluster heads associated with this transmission type, therefore it is not possible to associate WSN 1 with any number of cluster heads, and subsequently cannot relate it to the general criterion, *Complexity*. Thirdly, as the data is theoretically transmitted over only one possible route for each node, there is no ability or need for WSN 1 to relay data. Similarly, WSN 1 cannot be assessed to the general criterion *Resilience* as this criterion contains the basic criterion regarding the relaying of data, and WSN 1 does not have the ability to relay data between nodes. However, it can be included in the analysis for *Maintainability* as all basic criteria are relatable to WSN 1. The dotted and dashed connectors in Figure 6 outline the connections, in the hierarchy, from each WSN design.

3.5 Outline suitable evaluation grades.

Subjective judgements may be used to distinguish one alternative from another in terms of qualitative criteria. For example, to evaluate the *Maintainability* of a WSN some typical judgements may be that "*the maintainability of the WSN is poor, average or good*" (Yang & Xu, 2002) (Ren, et al., 2005). These five evaluation terms have been outlined, with H_n denoting the n^{th} evaluation grade. This is demonstrated by Equation 1:

$$H_n = \{Poor\ (H_1), Indifferent\ (H_2), Average\ (H_3), Good\ (H_4), Excellent\ (H_5)\} \tag{1}$$

3.6 Develop the belief degrees and criteria weights for MCDA analysis.

The weights of the criteria are calculated through Pairwise Comparison (PC) and Analytical Hierarchy Process (AHP), and are determined by qualitative assessment from expert judgement, using questionnaires. This step is

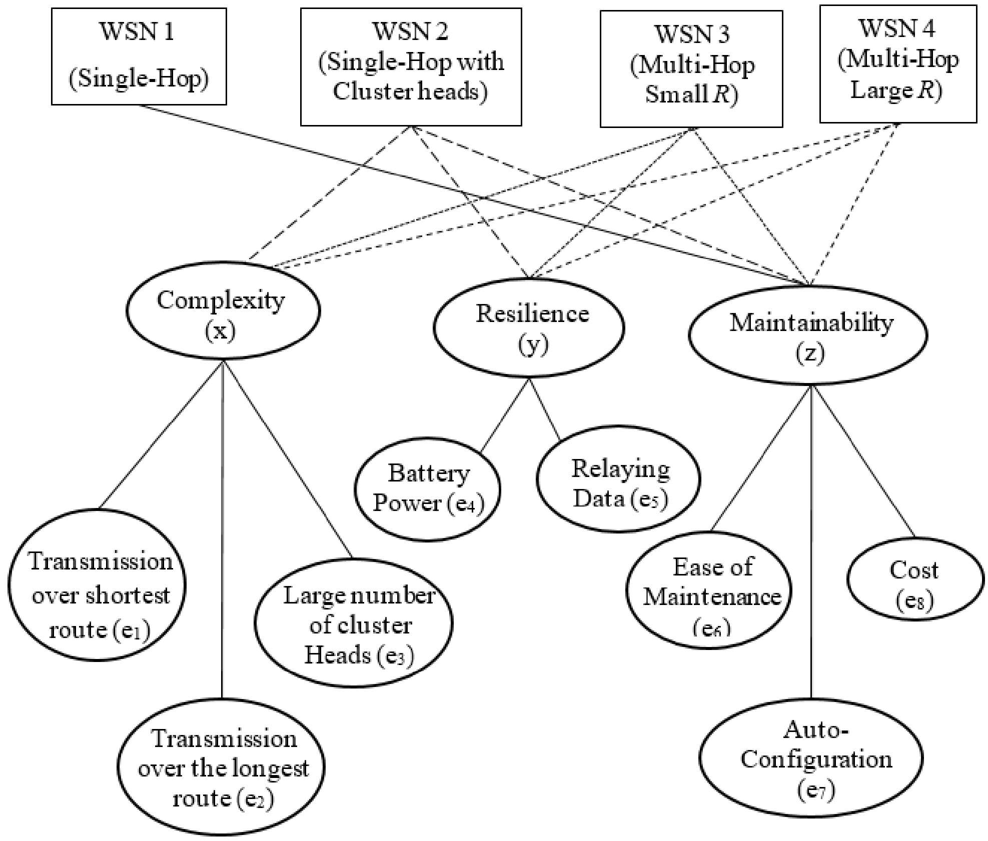

Figure 6: Evaluation Hierarchy for the four WSN designs

further outlined in the analysis in Section 4.1. PC and AHP are selected as they are efficient methods of applying a qualitative data gathering mechanism to a quantitative methodology. The method of utilising PC and AHP to determine subjective quantitative data for application in a relative weighting system is exceptionally useful in filling gaps in data for additional analysis techniques, such as with the ER or Bayesian Network approaches.

It is supposed that there is a simple two-level hierarchy. Suppose there are L basic criteria e_j $(j=1 \ldots L)$ associated with general criterion E. Similarly, suppose the normalised weights of each general criterion are given as ω_1, $\omega_2 \ldots \omega_i \ldots \omega_L$ $(i = 1 \ldots L)$ where, ω_i is the relative weight of the i^{th} general criterion (E_i) with $0 \leq \omega_i \leq 1$ and ω_{ij} is the weight of the basic criterion (e_i) $0 \leq \omega_{ij} \leq 1$, where j represents the j^{th} basic criterion under the i^{th} general criterion. For example, the weighing of general criterion, Complexity, is represented by ω_i and the weight of the 3rd basic criterion under logistics, (Large Number of Cluster Heads, e_3) is represented by ω_{13}. See Figure 6 which outlines the evaluation hierarchy and contains the allocated notation related to the weighting of criteria. Furthermore, let $\beta_{n,i}$ denote the belief degree of the basic criterion e_i to the evaluation grade H_n, where $\beta_{n,i} \geq 0$ and $\sum_{n=1}^{N} \beta_{n,i} = 1$ Finally, $S(e_i)$ is the assessment of an alternative under criterion e_i,. This assessment can be represented by Equation 2 (Yang & Xu, 2002) (Ren, et al., 2005) (Li & Liao, 2007) (Loughney, 2018).

$$S(e_i) = \{(H_n, \beta_{n,i}), n = 1, \ldots, N\} \;\; i = 1, \ldots, L \tag{2}$$

The assessment of a criterion, $S(e_i)$ is complete if the sum of the belief degrees is equal to 1, *i.e.* $\sum_{n=1}^{N} \beta_{n,i} = 1$.

3.7 Evidential Reasoning Algorithm and Data Aggregation

Suppose $m_{n,i}$ is the probability mass representing the degree to which e_i supports the hypothesis that the general criterion E is assessed to H_n, and is calculated by Equation 3 (Yang & Xu, 2002) (Li & Liao, 2007) (Loughney, 2018).

$$m_{n,i} = \omega_i \beta_{n,i} \quad n = 1, \dots, N \tag{3}$$

Similarly, for basic criteria, Equation 3 is rewritten as Equation 4:

$$m_{n,j} = \omega_{ij} \beta_{n,i} \quad n = 1, \dots, N \tag{4}$$

where, $m_{n,j}$ is the probability mass of the basic criteria e_j assessed to Hn. Also, $E_{I(j)}$ must be defined as the subset of the j basic criteria under the I^{th} general criterion, as given by Equation 5.

$$E_{I(j)} = \{e_1 \;\; e_2 \dots \; e_j\} \tag{5}$$

$m_{n,I(i)}$ is the probability mass defined as the degree to which all criteria in $E_{I(i)}$ support the hypothesis that E is assessed to the grade H_n. Similarly, $m_{H,\, I(i)}$ is the remaining probability mass which is unassigned to individual grades after all the basic criteria in $E_{I(i)}$ have been assessed. The terms $m_{n,I(i)}$ and $m_{H,\, I(i)}$ can be determined by combining the basic probability masses $m_{n,}$ and $m_{H,j}$ for all values of $n=1, \dots, N$ and $j=1, \dots, i$ (Yang & Xu, 2002) (Li & Liao, 2007) (Loughney, 2018). Thus, the Evidential Reasoning algorithm is expressed through Equations 6, 7, 8 & 9.

$$K_{I(i+1)} = \left[1 - \sum_{t=1}^{N} \sum_{\substack{z=1 \\ z \neq t}}^{N} m_{t,I(i)} m_{z,i+1}\right]^{-1} \quad i = 1, \dots, L-1 \tag{6}$$

$$m_{n,I(i+1)} = K_{I(i+1)} \begin{pmatrix} m_{n,I(i)} m_{n,i+1} + m_{n,I(i)} m_{H,i+1} \\ + m_{H,I(i)} m_{n,i+1} \end{pmatrix} \quad n = 1, \dots, N \tag{7}$$

$$m_{H,I(i+1)} = K_{I(i+1)} m_{H,I(i)} m_{H,i+1} \tag{8}$$

$$\beta_n = \frac{m_{n,I(L)}}{1 - m_{H,I(L)}}, \qquad n = 1, \dots, N, \qquad i = 1, \dots, L \tag{9}$$

where $K_{I(i+1)}$ is a normalising factor so that $\sum_{n=1}^{N} m_{n,I(i+1)} + m_{H,I(i+1)} = 1$ and β_n is the combined belief degree of the aggregated assessment for the criteria (Yang & Xu, 2002) (Li & Liao, 2007).

3.8 Utiliy Assessment and Ranking

The criteria must be ranked based upon their aggregated belief degrees from the ER algorithm. Suppose the utility of an evaluation grade, H_n, is denoted by $u(H_n)$. The utility of the evaluation grades are assumed to be equidistant as follows, with $u(H_1)=0$, $u(H_2)=0.25$, $u(H_3)=0.5$, $u(H_4)=0.75$ and $u(H_5)=1$ (Yang, 2001). The estimated utility for the general and basic criteria, $S(e_i)$, is given by Equation 9 (Yang & Xu, 2002) (Loughney, 2018):

$$u\big(S(e_i)\big) = \sum_{n=1}^{N} u(H_n)\beta_n\,(e_i) \tag{10}$$

3.9 Validation of the decision-making process.

Validation is a key aspect to the methodology, as it provides a reasonable amount of confidence to the results. In current literature, there is an axiom-based validation procedure, which is useful for validation of the process. The aggregation process may not be rational or meaningful if it does not follow certain axioms. The application of axioms is consistent with the partial validation procedure applied to the ER approach and is widely utilised in literature (Yang & Xu, 2002) (Durnbachm, 2012) (Loughney, 2018). The four axioms to be assessed are as follows:

- *Axiom 1.*
  A general criterion must not be assessed to H_n if the basic criteria are not assessed to H_n.
- *Axiom 2.*
  The general criterion should be precisely assessed to H_n, provided all basic criteria are assessed to H_n.
- *Axiom 3.*
  If all basic criteria, under a general criterion completely assessed to a given subset of evaluation grades, then the general criterion should be assessed to the same subset of grades.
- *Axiom 4.*
  If an assessment for basic criteria is incomplete, then the assessment for the general criterion should be incomplete to a certain degree.

4 CASE STUDY

4.1 Determining the Belief Degrees and Criterion Weights

In this section, the ER algorithm is applied to analyse the suitability of four different WSN designs for use in asset integrity monitoring of an offshore electrical power generator. The four WSN designs are based around the type of data transmission, they are as follows: Single-hop transmission, Single-hop transmission with cluster head nodes, Multi-hop transmission with a small sensor node radius and multi-hop transmission with a large sensor node radius. The four WSNs shall be denoted as WSN 1, WSN 2, WSN 3 and WSN 4 respectively.

Before the analysis can be conducted, the weights of each criterion, both general and basic must be determined and the belief degrees of the basic criteria must be determined based upon a set of evaluation grades. The weights of the criteria are calculated through PC and AHP, and both the weights and the belief degrees are determined by qualitative assessment from expert judgement, through the use of questionnaires.

As outlined previously, three general suitability criteria are considered, which are Complexity, Resilience and Maintainability. These criteria are generic and difficult to assess directly, therefore, lower-level criteria are required. The evaluation hierarchy is shown in Figure 6, along with the notation for each criterion and their weights (ω_i and ω_{ij}).

Similarly, the belief degrees must be determined against the evaluation grades for each basic criterion. Five experts and their judgements were used to complete the qualitative questionnaire across disciplines of offshore engineering and computer science. This allowed for a more comprehensive view point as the designs of the WSNs are to be used on-board an offshore platform. The five experts are to remain anonymous, however, their expertise and experience are outlined as follows:

Expert 1 is currently an employee of a leading classification society and holds a university qualification at the MSc. Level. This person has 8 years of experience at sea and more than 5 years as an offshore safety manager.

Expert 2 is currently an employee of a leading provider of risk management services and holds a university qualification at Ph.D level. This person has 10 years of experience as an offshore technical director.

Expert 3 is currently a CEO of a leading energy service and holds a university qualification at Ph.D level.

Expert 4 is currently an employee of a UK university as a senior lecturer and researcher. This person has 10 years' experience in research areas involving the progression of the Internet of Things and interdisciplinary technologies. This person also holds a university qualification at Ph.D level.

Expert 5 is currently an employee of a UK university as a senior lecturer and researcher. This person has 10 years' experience in research areas involving the progression of the Internet of Things and Computer, communication and control technologies. This person also holds a university qualification at Ph.D level.

The PC and AHP methodologies and calculations are not demonstrated in this paper, however some applications and examples can be found in the following studies (Loughney & Wang, 2017) (Saaty, 1980) (Saaty, 1990) (Saaty, 1994) (Ahmed, et al., 2005) (Koczkodaj & Szybowski, 2015).

However, the Consistency Ratios (CR) of the PC and AHP analyses can be stated for completeness. The CR value of the main criteria (*x*, *y*, and *z*) was calculated as 0.011. This means that the degree of consistency within the pairwise comparison is acceptable as the CR value is less than 0.10. Similar calculations were conducted for the other sub-criteria in the PC, with the other CRs calculated as 0.01 for the *Complexity* criteria (e_1, e_2 and e_3), and 0.06 for the *Maintainability* criteria (e_6, e_7 and e_8). These again are acceptable as they are less than 0.10. CR calculations are not possible for matrices of less than 2×2 as the Saaty RI values for 2×2 matrices are zero. This is the case with the *Resilience* criteria (e_4 and e_5). Utilising the PC and AHP methods, the weights for all of the basic and general criteria are calculated and are demonstrated in Table 2.

Table 2: Calculated weights for the general and basic attribute for use in the ER algorithm

x			y		z			SUM
21.34%			49.86%		28.80%			100.00%
e1	e2	e3	e4	e5	e6	e7	e8	
53.09%	16.18%	30.73%	65.08%	34.92%	53.62%	20.46%	25.92%	
SUM			SUM		SUM			
100.00%			100.00%		100.00%			

Each of the five experts completed the questionnaire which allowed for the completion of the belief degrees for the basic criteria. The hierarchy and normalised weights of all criteria is demonstrated in Table 3 as well as the completed belief degrees for each basic criterion.

Table 3: Generalised decision matrix for WSN suitability assessment with relative weights and basic attribute belief degrees

General Attributes	Basic Attributes	WSN 1 Single-Hop	WSN 2 Single Hop (Cluster)	WSN 3 Multi-Hop (Small Radius)	WSN 4 Multi-Hop (Large Radius)	Evaluation Grades	
Complexity (x) (ω_1 = 0.2134)	Transmission over the shortest route (e_1) (ω_{11} = 0.5309)		0.6	0.2	0.2	H_1	Poor
				0.2		H_2	Indifferent
			0.4	0.6	0.2	H_3	Average
						H_4	Good
					0.6	H_5	Excellent
	Transmission over the longest route (e_2) (ω_{12} = 0.1618)			0.4	0.8	H_1	
				0.2		H_2	
			0.6	0.4	0.2	H_3	
						H_4	
			0.4			H_5	

	Large number of Cluster nodes (e_3) (ω_{13} = 0.3073)		0.6	0.2	0.6	H_1
						H_2
				0.2	0.3	H_3
			0.2	0.2	0.1	H_4
			0.2	0.4		H_5
Resilience (y) (ω_2 = 0.4986)	Battery Power (e_4) (ω_{21} = 0.6508)				0.2	H_1
			0.2	0.2		H_2
			0.2			H_3
			0.4	0.2	0.2	H_4
			0.2	0.6	0.6	H_5
	Relaying Data (e_5) (ω_{22} = 0.3492)		0.2			H_1
						H_2
				0.2	0.4	H_3
			0.2			H_4
			0.6	0.8	0.6	H_5
Maintainability (z) (ω_3 = 0.288)	Ease of Maintenance (e_6) (ω_{31} = 0.53.62)			0.2	0.4	H_1
			0.4			H_2
			0.2	0.4		H_3
		0.5	0.4	0.4	0.4	H_4
		0.5			0.2	H_5
	Auto-Configuration (e_7) (ω_{32} = 0.2064)			0.2	0.4	H_1
		0.2	0.2			H_2
		0.2	0.4	0.4	0.4	H_3
		0.2	0.4	0.2		H_4
		0.4		0.2	0.2	H_5
	Cost (e_8) (ω_{33} = 0.2592)	0.2		0.4	0.4	H_1
			0.4			H_2
		0.2	0.4			H_3
		0.6		0.6	0.2	H_4
			0.2		0.4	H_5

4.2 Aggregation Assessment through Evidential Reasoning Algorithm

The problem now is how the judgements in Table 3 can be aggregated to arrive at an assessment as to the best suited WSN for asset integrity monitoring on and offshore platform. To demonstrate the procedure of the ER algorithm the detailed steps of the calculation shall be shown for generating the assessment for the WSN 3's Complexity (*y*), by aggregating the three basic criteria Transmission over shortest route (e_1), Transmission over the longest route (e_2) and large number of cluster nodes (e_3). The evaluation grades have been defined in Equation 1. From Table 3 and Equation 2 the following can be stated:

$$\beta_{1,1} = 0.2, \quad \beta_{2,1} = 0.2, \quad \beta_{3,1} = 0.6, \quad \beta_{4,1} = 0, \quad \beta_{5,1} = 0$$

$$\beta_{1,2} = 0.4, \quad \beta_{2,2} = 0.2, \quad \beta_{3,2} = 0.4, \quad \beta_{4,2} = 0, \quad \beta_{5,2} = 0$$

$$\beta_{1,3} = 0.2, \quad \beta_{2,3} = 0, \quad \beta_{3,3} = 0.2, \quad \beta_{4,3} = 0.2, \quad \beta_{5,3} = 0.4$$

As the weight have been calculated the basic probability masses can be calculated utilising Equations 3 and 4.

$$m_{1,1} = 0.2 \times 0.5309, \quad m_{2,1} = 0.2 \times 0.5309, \quad m_{3,1} = 0.6 \times 0.5309, \quad m_{4,1} = 0, \quad m_{5,1} = 0,$$
$$\sum_{n=1}^{N} m_{n,1} = 0.531, \quad \therefore m_{H,1} = 0.469$$

$$m_{1,2} = 0.4 \times 0.1618, \quad m_{2,2} = 0.2 \times 0.1618, \quad m_{3,2} = 0.4 \times 0.1618, \quad m_{4,2} = 0, \quad m_{5,2} = 0,$$
$$\sum_{n=1}^{N} m_{n,2} = 0.162, \quad \therefore m_{H,2} = 0.0.838$$

$$m_{1,3} = 0.2 \times 0.3073, \quad m_{2,3} = 0, \quad m_{3,3} = 0.2 \times 0.3073, \quad m_{4,3} = 0.2 \times 0.3073,$$
$$m_{5,3} = 0.4 \times 0.3073, \quad \sum_{n=1}^{N} m_{n,3} = 0.307, \quad \therefore m_{H,3} = 0.693$$

It is now possible to use Equations 6, 7 and 8 to calculate the combined probability masses. Firstly, criteria e_1 and e_2 are to be aggregated. Equation 6 is solved in stages to find $K_{I(2)}$.

$$\sum_{\substack{t=1 \\ j \neq t}}^{5} m_{t,I(1)} m_{j,2} = (m_{1,1}m_{2,2}) + (m_{1,1}m_{3,2}) + (m_{1,1}m_{4,2}) + (m_{1,1}m_{5,2})$$
$$= ((0.2 \times 0.5309).(0.2 \times 0.1618)) + ((0.2 \times 0.5309).(0.4 \times 0.1618)) + (0) + (0)$$
$$= 0.01031$$

$$\sum_{\substack{t=2 \\ j \neq t}}^{5} m_{t,I(1)} m_{j,2} = (m_{2,1}m_{1,2}) + (m_{2,1}m_{3,2}) + (m_{2,1}m_{4,2}) + (m_{2,1}m_{5,2})$$
$$= ((0.2 \times 0.5309).(0.4 \times 0.1618)) + ((0.2 \times 0.5309).(0.4 \times 0.1618)) + (0) + (0)$$
$$= 0.01374$$

$$\sum_{\substack{t=3 \\ j \neq t}}^{5} m_{t,I(1)} m_{j,2} = (m_{3,1}m_{1,2}) + (m_{3,1}m_{2,2}) + (m_{3,1}m_{4,2}) + (m_{3,1}m_{5,2})$$
$$= ((0.6 \times 0.5309).(0.4 \times 0.1618)) + ((0.6 \times 0.5309).(0.2 \times 0.1618)) + (0) + (0)$$
$$= 0.03092$$

$$\sum_{\substack{t=4 \\ j \neq t}}^{5} m_{t,I(1)} m_{j,2} = (m_{4,1}m_{1,2}) + (m_{4,1}m_{2,2}) + (m_{4,1}m_{3,2}) + (m_{4,1}m_{5,2}) = (0) + (0) + (0) + (0) = 0$$

$$\sum_{\substack{t=5 \\ j \neq t}}^{5} m_{t,I(1)} m_{j,2} = (m_{5,1}m_{1,2}) + (m_{5,1}m_{2,2}) + (m_{5,1}m_{3,2}) + (m_{5,1}m_{4,2}) = (0) + (0) + (0) + (0) = 0$$

$$K_{I(2)} = [1 - (0.01031 + 0.01374 + 0.03092)]^{-1} = 1.058$$

Given that the value of $K_{I(2)}$ has been determined Equations 7 and 8 can now be utilised, along with the basic probability masses.

$$m_{1,I(2)} = K_{I(2)}\left(m_{1,1}m_{1,2} + m_{1,1}m_{H,2} + m_{H,1}m_{1,2}\right) = 0.1335$$

$$m_{2,I(2)} = K_{I(2)}\left(m_{2,1}m_{2,2} + m_{2,1}m_{H,2} + m_{H,1}m_{2,2}\right) = 0.1138$$

$$m_{3,I(2)} = K_{I(2)}\left(m_{3,1}m_{3,2} + m_{3,1}m_{H,2} + m_{H,1}m_{3,2}\right) = 0.3364$$

$$m_{4,I(2)} = K_{I(2)}\left(m_{4,1}m_{4,2} + m_{4,1}m_{H,2} + m_{H,1}m_{4,2}\right) = 0$$

$$m_{5,I(2)} = K_{I(2)}\left(m_{5,1}m_{5,2} + m_{5,1}m_{H,2} + m_{H,1}m_{5,2}\right) = 0$$

$$m_{H,I(2)} = K_{I(2)}m_{H,1}m_{H,2} = 0.4161$$

The first two basic criteria, e_1 and e_2, have been aggregated, and it is possible to combine the above results with the third criterion e_3. This calculation is the same as above however it utilises the subjective data in Table 3 for the criterion e_3 and the probability masses calculated above.

Given the results of the aggregation, the assessment for the Complexity of WSN 3 by aggregating Transmission over the shortest route (e_1), Transmission over the longest route (e_2) and large number of cluster heads (e_3), is given by:

$$S(Complexity) = S(e_1 \oplus e_2 \oplus e_3) = \{(Poor, 0.225), (Indifferent, 0.141), (Average, 0.498),$$
$$(Good, 0.046), (Excellent, 0.091)\}$$

It is important to note that changing the aggregation order does not change the final results in any way.

4.3 Results and Analysis of ER aggregation

The calculations demonstrated in Section 4.1 for the assessment of WSN 3 in terms of its *Complexity* were repeated for the other basic criteria for each of the proposed WSNs. The results were then aggregated further to give the overall beliefs for the general criteria for each of the WSNs. All of the calculations were completed using Microsoft Excel as it provided a simple way of inputting the ER algorithm and displaying the results clearly. Table 4 shows the aggregated assessment for the general criteria for each WSN design.

From Table 4 it is possible to distinguish some of the differences between the WSNs and rank them. However, this can be very difficult, for example, it is difficult to determine the most suitable WSN in terms of complexity. Similarly, in the only case where WSN 1 is assessed, under the criterion *Maintainability*, it is the best performing WSN design as its highest-ranking beliefs are across the evaluation grades of *good* and *excellent*. However, WSN 1 cannot be assessed in *Complexity* or *Resilience* as it is a very simple design in terms of its data transmission. It therefore makes sense that WSN 1 performs better than the other WSNs in terms of

Maintainability. Furthermore, it can be seen that in terms of *Resilience* both WSNs 3 and 4 outperform WSN 2. However, it is difficult to determine which of the WSN designs perform better in terms of their resilience.

Table 4: Aggregated belief structure for the general attributes for each WSN

General Attributes	WSN 1 Single-Hop	WSN 2 Single Hop (Cluster)	WSN 3 Multi-Hop (Small Radius)	WSN 4 Multi-Hop (Large Radius)	Evaluation Grades	
Complexity (ω_1 - 21.34%)		0.561	0.225	0.405	H_1	Poor
		0.000	0.141	0.000	H_2	Indifferent
		0.309	0.498	0.226	H_3	Average
		0.044	0.046	0.123	H_4	Good
		0.086	0.091	0.342	H_5	Excellent
Resilience (ω_2 - 49.86%)		0.041	0.000	0.135	H_1	
		0.143	0.129	0.000	H_2	
		0.143	0.037	0.078	H_3	
		0.359	0.129	0.135	H_4	
		0.313	0.704	0.652	H_5	
Maintainability (ω_3 - 28.80%)	0.035	0.000	0.238	0.423	H_1	
	0.026	0.380	0.000	0.000	H_2	
	0.063	0.276	0.306	0.052	H_3	
	0.505	0.309	0.430	0.285	H_4	
	0.371	0.035	0.026	0.240	H_5	

Continuing the procedure of ranking the WSNs, it is necessary to determine their overall performance and suitability for offshore use. This is done by aggregating the general criteria still further using the ER algorithm. This demonstrates the overall suitability of WSNs 2, 3 and 4. Table 5 and Figure 7 demonstrate overall suitability beliefs for the WSN configurations.

It can be seen by Figure 7 that it is difficult to ascertain the most suitable WSN configuration for use for offshore asset integrity monitoring. However, what can be said is that WSNs 3 and 4 just outperform WSN 2 as they both have their highest beliefs at the top evaluation grade, e*xcellent*. In order to more accurately rank the WSNs in terms of their performance and suitability, the utility estimation analysis outlined in Section 4.2, by Equations 13 and 14, shall be applied further to determine the ranking of each WSN.

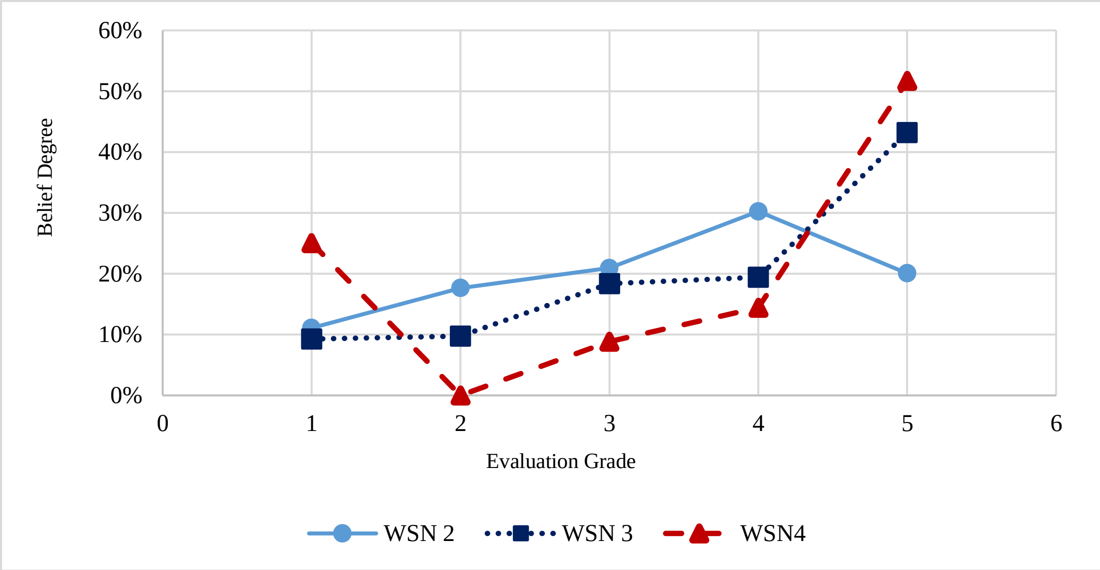

Figure 7: Graph showing the overall aggregated assessment for the WSNs (1=Poor, 2=Indifferent, 3=Average, 4=Good, 5=Excellent)

4.3.1 Utility Ranking

The WSN designs can be ranked based upon their aggregated belief degrees from the ER algorithm, and this can be done through utility assessment. If there is not preference information available then the values of $u(H_n)$ can be assumed to be equidistant, as outlined in Section 3.8. The estimated utility for the general and basic criteria, $S(z(e_i))$, given the set of evaluation grades, is given by Equation 10.

Equation 10 can be used as it is because the belief degrees sum to equal 1, therefore there can be no upper or lower bound limit on the utility estimation, just one utility value for each WSN. Each WSN can be ranked both in terms of each general criterion and the overall suitability of the WSNs. By applying Equation 10 and the data in Table 5 to the general criterion Complexity for WSN 3, its utility score can be determined.

$$u\big(S(Complexity)\big) = (u(H_1)\beta_1) + (u(H_2)\beta_2) + (u(H_3)\beta_3) + (u(H_4)\beta_4) + (u(H_5)\beta_6)$$
$$= (0 \times 0.2225) + (0.25 \times 0.141) + (0.5 \times 0.498) + (0.75 \times 0.046) + (1 \times 0.91) = 0.409$$

The utility estimation is calculated the same way for each WSN given each general criterion, and for the overall suitability for each WSN. These results are tabulated and the WSNs can be ranked accordingly.

Table 6 shows that WSN 4 performs better in terms of the network's ability to deal with complex transmissions and connections, with WSN 3 fairing much better than WSN 2. In terms of their ability to deal with complex transmissions and connections the WSNs are ranked as follows:

Table 5: Utility values and ranking of WSNs 2, 3 and 4 for the general attribute complexity.

Complexity (x) belief					
Grades		u(Grades)	WSN 2	WSN 3	WSN 4
H1	Poor	0	0.561	0.225	0.405
H2	Indifferent	0.25	0.000	0.141	0.000
H3	Average	0.5	0.309	0.498	0.226
H4	Good	0.75	0.044	0.046	0.023
H5	Excellent	1	0.086	0.091	0.347
		u(Total)	0.274	0.409	0.477
		Ranking	3	2	1

$$WSN\ 4 > WSN\ 3 > WSN\ 2$$

The ranking order of the WSNs for the criterion Resilience is as follows:

$$WSN\ 3 > WSN\ 4 > WSN\ 2$$

Continuing on with the ranking of the WSNs based on their performance against each general criterion, the utility values were calculated for Maintainability. WSN 1 outperforms WSNs 2, 3 and 4 in terms of their capabilities as an easily maintainable network. The ranking of the WSNs in terms of maintainability are as follows:

$$WSN\ 1 > WSN\ 3 > WSN\ 2 > WSN\ 4$$

Finally, the WSNs are ranked based upon their overall performance, with the exception of WSN 1 which cannot be included as it was not assessed against general criteria complexity and resilience. Based upon the utility ranking for the overall suitability, WSN 3 was determined to be the most suitable design and data transmission choice for offshore applications. This provides some clarity to the analysis of Figure 7 where it could not be seen whether WSN 3 or WSN 4 would be the most suitable configuration based upon the analysis. The ranking order for overall suitability is as follows:

$$WSN\ 3 > WSN\ 4 > WSN\ 2$$

4.3.2 Results comparison of calculated weights and normalised weights

In addition to the analysis presented in Sections 4.1 and 4.2, further calculations were conducted in order to compare the calculated weights of the criteria with a normalised set of weights. In this case normalising the weights mean evenly distributing the values from 100%. For example, in the event that the weights are normalised, the weights of the main criteria would all equal 1/3 (33.33%). In theory, the application of calculated weights through expert judgement and AHP analysis should prove to be more accurate than the method of normalising the relative weights of criteria. Table 7 shows the utility values and rankings of each WSN against the general criteria and the final overall assessment for both the calculated weights and the normalised weights.

It is immediately apparent from Table 7 that the utility values and ranks of the WSNs are not completely the same for normalised weights as they are for calculated weights. If the complexity criterion is highlighted it can be seen that the ranks are slightly different. For the normalised weighting system WSN 3 performs the best with WSN 4 performing the worst. However, when the calculated weights method is used, WSN 4 is apparently the most preferred method of data transmission. Furthermore, the utility values for the normalised weight method show very little difference in terms of the actual values: 0.404, 0.409 and 0.306 for WSNs 2, 3 and 4 respectively. However, when the calculated weights are used, the utility values differ much more drastically; 0.274, 0.409 and 0.477 for WSNs 2, 3 and 4 respectively. This shows that the equal assignment of weights has a large effect on the outcomes of the ranking estimations. Typically, one would expect WSNs 3 and 4 to be able to cope much better with more complex data transmissions than WSN 2 (Mhatre & Rosenberg, 2004) (Fischione, 2014). This pattern is demonstrated throughout Table 7, particularly in the overall suitability ranking. Therefore it is possible to state that utliising calculated weights as opposed to normalised weights generates more accurate results when compared against real world applications.

Table 6: Utility estimations and ranks of each WSN for the general attributes and overall assessment for normalised weights and calculated weights

	WSN 1	WSN 2	WSN 3	WSN 4
Complexity (*x*)				
Normalised				
u(Total)	-	0.404	0.409	0.306
Ranking	-	2	1	3
Calculated				
u(Total)	-	0.274	0.409	0.477
Ranking	-	3	2	1
Resilience (*y*)				
Normalised				
u(Total)	-	0.718	0.879	0.809
Ranking	-	3	1	2
Calculated				
u(Total)	-	0.690	0.852	0.792
Ranking	-	3	1	2
Maintainability (*z*)				
Normalised				
u(Total)	0.719	0.508	0.502	0.466
Ranking	1	2	3	4
Calculated				
u(Total)	0.788	0.500	0.501	0.480
Ranking	1	3	2	4
Overall				
Normalised				
u(Total)	-	0.550	0.597	0.525
Ranking	-	2	1	3
Calculated				
u(Total)	-	0.576	0.694	0.669
Ranking	-	3	1	2

4.4 Partial Validation

In order to verify the method of applying the ER algorithm to the decision-making process, it must first satisfy the four axioms stated in Section 3.10. The overall beliefs and the general criterion beliefs are very much reliant on the magnitude of the belief degrees of the basic criteria. Each axiom shall be identified, and cross examined individually.

- *The independence axiom*: where a general criterion must not be assessed to an evaluation grade, H_n, if none of the basic criteria, under the general criterion, are assessed to H_n.. This axiom can be said to be satisfied because when the aggregation of the general criterion *maintainability* is analysed, for WSN 2. It can be seen that none of the basic criteria are assessed to the grade *poor*, *i.e.* $\beta_{n,\,i} = 0$ for $i = 1, \ldots, L$. Because of this, the belief degree of the evaluation grade, *indifferent*, for the general criterion maintainability, should also be equal to 0, *i.e.* $\beta_{n,} = 0$, and it is. Hence, in this instance the independence axiom is satisfied.
- *The consensus axiom*: where the general criteria should be precisely assessed to a grade H_n, if all of the basic criteria in E are assessed to H_n. This axiom can be said to be satisfied by the example of the aggregation of the basic criteria of *Maintainability* for WSN 2. The initial belief degrees for the evaluation grades, *poor, indifferent* and *excellent* of the basic criteria e_6, e_7 and e_8 are *poor (0, 0, 0), indifferent (0.4, 0.2, 0.4,)* and *excellent (0, 0, 0.2)* respectively. For the three basic criteria, there are similar values of belief degree. The axiom is satisfied, in this case, by the aggregated belief degree of the basic criteria for the grades *poor, indifferent* and *excellent*, which are *poor (0.000), indifferent (0.380)* and *excellent (0.035)*. This trend can be seen across all of the data aggregation for all of the criteria. Hence, the ER analysis satisfies the consensus axiom.
- *The completeness axiom*: where if all basic criteria, under a general criterion, are completely assessed to a subset of evaluation grades, then the general criteria should be completely assessed to the same subset of grades. This is true throughout the entire analysis whereby all criteria are assessed to the same set of evaluation grades of: *poor, indifferent, average, good* and *excellent*. Therefore this axiom can be said to be satisfied.
- *The incompleteness axiom*: where if an assessment for any basic criterion in E is incomplete, then the assessment for the general criterion should be incomplete to a certain degree. This is consistent throughout the analysis as there are not any incomplete belief degrees, and all belief degrees sum to equal one for each criterion. This can be seen throughout the entire analysis. The initial belief degrees for the basic criteria sum to one for each criterion. Subsequently, the aggregated belief degrees for the general criteria also sum to equal one, and finally, the overall assessment beliefs for each WSN also sum to one. Therefore, there are no incomplete assessments and the axiom can be said to be satisfied.

Having satisfied the four outlined axioms for the ER algorithm, it can be said that the methodology and process are partially validated.

5 DISCUSSION

While the analysis presented in this research proved to be conclusive, there is still room for improvement. The initial designs of the wireless sensor networks are only concerned with hardware and transmission configurations and not any software at all. Immediately this is an area for improvement. The software plays a key role in the operation and resilience of a WSN, in terms of the data that can be detected and transmitted and the issue of cyber-protection. The authors feel that further study is need in the area of software design and selection, in relation to the designs and assessment outlined in this research.

In terms of the decision-making algorithm, there are a number of areas that would benefit from further work and improvement. Initially the assessment contains eight basic criteria and three general criteria, which can be extended given the application of software analysis. This would inevitably make the analysis and results much more coherent, by covering the comparison of a number of WSN designs based upon the application of software. It is also possible to apply a larger selection of evaluation grades. In this work five evaluation grades were used to reduce complexity in the decision-making algorithm, but more grades can be utilised. For example, Ren, *et al.* (2014) apply the use of three different evaluation grading systems for three risk assessment areas. Each evaluation grading system contains seven evaluation grades. This provides a much more accurate generation of the basic criteria belief degrees. However, utilising an increased number of evaluation grades requires further aggregation through the use of fuzzy reasoning.

A further path to expand upon the decision-making within this research is to apply extended ER algorithms to the outline situation. One unique ER rule in particular has been developed by Yang & Xu (2013). Their research establishes a unique ER rule to combine multiple pieces of independent evidence conjunctively with weights and reliabilities. They propose a novel concept of Weighted Belief Distribution (WBD) extended to WBD with Reliability (WBDR) to characterise evidence in complement of Belief Distribution (BD) introduced in the D–S theory of evidence. Hence, the new ER rule constitutes a generic conjunctive probabilistic reasoning process, which is applicable to combine multiple pieces of independent evidence with different weights and reliabilities in a wide range of areas such as multiple criteria decision analysis. Application of this ER rule could improve the analysis as it can determine if there is conflict between subjective information sources, and hence one may be reliable. In the event that two pieces of evidence conflict, the weighted average rule is applied to the belief degrees and in theory increases the reliability of the belief degrees (Yang & Xu, 2013).

6 CONCLUSION

Real world decision problems and assessments are often complex and involve multiple criteria with high uncertainty. Hence, it is essential to conduct a coherent, rational, reliable, and transparent decision analysis. This research investigated the possible configurations and designs of WSNs that could feasibly operate within an offshore electrical power generator for the purpose of asset integrity monitoring. A set of qualitative criteria and criteria were outlined to assist with the decision. Similarly, the ER approach was investigated and utilised for the purpose of determining the most suitable WSN design by aggregating the multiple criteria.

The ER approach establishes a nonlinear relationship between an aggregated assessment for general criteria and an original assessment of basic criteria. The numerical analysis of the research dealt with the design selection problem outlined previously with key information and data taken from literature and expert judgements. It demonstrated that the ER approach could accurately be used as a viable decision-making tool in the design selection of WSN. Furthermore, the application of estimated weights and calculated weights demonstrates how sensitive the ER algorithm is to changes in initial data entries. From the analysis, it is clear that the ER approach can be applied to a number of MCDA problems with or without uncertainty.

This research set out to outline a number of WSN configurations for use in the offshore industry and determine the most suitable based upon a set of design criteria. Four WSN configurations were proposed: i) WSN 1 – Single-hop, ii) WSN 2 – Single-hop with cluster nodes, iii) WSN 3 – Multi-hop with a small sensor radius, and iv) WSN 4 – Multi-hop with a large sensor radius. Following this a qualitative evaluation hierarchy was established to further solve the decision-making problem, *i.e.* which WSN would be most suitable for application within an electrical power generation module. The ER approach was applied to each of the WSNs based upon the outlined evaluation hierarchy. The subsequent analysis determined that a multi-hop configuration with a small sensor radius (WSN 3) would be the optimum solution to asset integrity monitoring of an offshore, gas turbine driven electrical generator.

DECLARATION OF CONFLICTING INTERESTS

The author(s) declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: This paper is the opinion of the authors and does not represent the belief and policy of their employers.

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REFERENCES

Ahmed, A. et al., 2005. Application of Analytical Hierarchy Process and Bayesian Belief Networks for Risk analysis. *Complexity International,* Volume 12, pp. 1-10.

Akhondi, M., Carlsen, S. & Petersen, S., 2010. Applications of Wireless Sensor Networks in the Oil, Gas and Resource Industry. *24th IEEE International Conference on Advanced Information Networking and Applications,* pp. 941-948.

Anand, V. & Pandey, S., 2020. New approach of GA–PSO-based clustering and routing in wireless sensor networks. *Int J Commun Syst,* Volume 33, p. https://doi.org/10.1002/dac.4571.

Carlsen, S., Petersen, S., Skavhaug, A. & Doyle, P., 2008. Using Wireless Sensor networks to Enable Increased Oil Recovery. *Proceedings of the 13th IEEE International COnference on Emerging Technologies and Factory Automation.*

Chandrasekaran, S., Chithambaram, T. & Khader, S. A., 2016. Structural Health Monitoring of Offshore Structures Using Wireless Sensor Networking under Operational and Environmental Variability. *International Journal of Environmental, Chemical, Ecologiical, Geological and Geophysical Engineering,* 10(1).

Chen, S., Liu, J., Wang, H. & Augusto, 2013. *An evidential reasoning based approach for decsion making with partially ordered preference under uuncertainty.* Tianjin, Proceedings of the 2013 International Conference on Machine Learning and Cybernetics.

Chen, S. et al., 2018. Evidential reasoning with discrete belief structures. *Information Fusion,* Volume 41, pp. 91 - 104.

Chhaya, L., Sharma, P., Bhagwatikar, G. & Kumar, A., 2017. Wireless Sensor Network Based Smart Grid Communiications: Cyber Attacks, Intrusion Detection System and Topology Control. *Electronics,* 6(5).

Chong, C. Y. & Kumar, S. P., 2003. Sensor Networks: Evolution, Opportunities and Challenges. *Proceedings of the IEEE,* 91(8), pp. 1247-1256.

Coutinho, R. W. L., Boukerche, A., Vieira, L. F. M. & Loureiro, A. A. F., 2018. Underwater Wireless Sensor Networks: A New Challenge for Topology Control–Based Systems. *ACM Comput. Surv,* 51(1), pp. 1 - 36.

Cresswell, J., 2010. *Restoring Heart to Thistle Platform through rig revamp.* [Online]
Available at: https://www.energyvoice.com/oilandgas/23235/restoring-heart-to-thistle-platform-through-rig-revamp/
[Accessed May 2015].

Durnbachm, I. N., 2012. An empirical test of the evidential reasoning approach's synthesis axioms. *Expert Systems with Applications,* 39(12), pp. 11048 - 11054.

Du, Y. & Zhong, J., 2021. Generalized combination rule for evidential reasoning approach and Dempster–Shafer theory of evidence. *Information Sciences,* Volume 547, pp. 1201 - 1232.

Ferreira, V. & Alves da Silva, A., 2007. Toward Estimating Autonomous Neural Network-based Electric Load Forcasters. *IEEE Transactions on Power Systems,* 22(4), pp. 1554-1562.

Fischione, C., 2014. *An Introduction to Wireless Sensor Networks,* Stockholm: KTH, Royal Institute of Technology.

Fu, C., Chang, W., Xu, D. & Yang, S., 2019. An evidential reasoning approach based on criterion reliability and solution reliability. *Computers & Industrial Engineering,* Volume 128, pp. 401 - 417.

Gao, T. et al., 2010. energy-efficient cluster head selection scheme based on multiple criteria decision making for wireless sensor networks. *Wireless Personnal Communications,* Volume 63, pp. 871-894.

Gupta, P. & Kumar, P., 1998. Critical Power for Asymptotic Connectivity in Wireless Systems. *Stochastic Analysis, Control, Optimisation and Applications,* pp. 547-566.

Halter, M., Gurganious, D. & Chi, C., 2012. *Industrial Wireless Sensor Networks: A Market Dynamics Report.* ON World.

Haque, M. E. & Baroundi, U., 2021. Ambient self-powered cluster-based wireless sensor networks for industry 4.0 applications. *Soft Computing,* Volume 25, p. 1859–1884.

Harrop, P. & Raghu, D., 2018. *Wireless Sensor Networks (WSN) 2014-2024: Forecasts, Technologies, Players,* IDTechEX.

HSE, 2014. *Statistics - Offshore Hydrocarbon Releases 1992 - 2015.* [Online]
Available at: http://www.hse.gov.uk/offshore/statistics.htm
[Accessed December 2015].

HVPD, 2016. *An Introduction to Partial Discharge.* [Online]
Available at: http://www.HVPD.co.uk/technical
[Accessed 6 2017].

IEC, I. E. C., 2014. *Internet of Things: Wireless Sensor Networks (White Paper),* Geneva, Switzerland.

Jiang, S., Janf, W. S. & Skibniewski, M. J., 2012. Selection of wireless technology for tracking construction materials using a fuzzy decision model. *Journal of Civil Engineering and Management,* 18(1), pp. 43-59.

Jia, Q., Hu, J. & Zhang, W., 2020. A Novel Fault Detection Model Based on Atanassov's Interval-Valued Intuitionistic Fuzzy Sets, Belief Rule Base and Evidential Reasoning. *IEEE Access,* Volume 8, pp. 4551 - 4567.

Kiameh, P., 2003. Chapter 13: Gas Turbine Instrumentation and Control systems. In: *Power generation Handbook: Selection, Applications, Operations and Maintenance.* s.l.:McGraw-Hill.

Klein, M., 2012. Emissions Control for Gas Turbines. *Decentralized Energy,* 13(2).

Koczkodaj, W. & Szybowski, J., 2015. Pairwise Comparison Simplified. *Applied Mathematics and Computation,* Volume 253, pp. 387-394.

Kumar, S. & Chaurasiya, V. K., 2018. Amultisensor data fusion strategy for path selection in Internet-of-Things oriented wireless sensor network (WSN). *Concurrency Computat Pract Exper,* Volume 30, pp. 1-14.

Lajoie, A., 2010. *How Wireless Sensing can Benefit Offshore.* [Online]
Available at: http://www.offshore-mag.com/articles/print/volume-70/issue-9/production-operations/how-wireless-sensing-can-benefit-offshore.html
[Accessed 06 2017].

Li, Y. & Liao, X., 2007. Decision support for risk analysis on dynamic alliance. *Decision support systems,* Volume 42, pp. 2043-2059.

Loughney, S., 2018. *Asset Integrity Case Development for Normally Unattended Offshore Installations.* Liverpool: Doctoral Thesis, Liverpool John Moores University.

Loughney, S., Davies, P. A. & Wang, J., 2017. *Bayesian network modelling for offshore installations: Gas turbine fuel gas release with potential fire and explosion consequences.* ESREL 2017, Portorož, Slovenia., Safety and Reliability. Theory and Applications – Cepin & Bris Hardback (Eds). 2017 Taylor & Francis Group, London, ISBN 978-1-138-62937-0. May 25, 2017.

Loughney, S. & Wang, J., 2017. Bayesian network modelling of an offshore electrical generation system for applications within an asset integrity case for normally unattended offshore installations. *Proc. IMechE. Part M: J. Engineering for the Maritime environment,* Volume (online), pp. 1-19 .

Lu, S. et al., 2018. Condition monitoring and fault diagnosis of motor bearings using undersampled vibration signals from a wireless sensor network. *Journal of Sound and Vibration,* Volume 414, pp. 81-96.

Meggitt, 2016. *Gas turbine Sensing and Monitoring.* [Online]
Available at: http://www.meggittsensingsystems.com
[Accessed 3 2017].

Mhatre, V. & Rosenberg, C., 2004. Design Guidelines for Wireless Sensor Networks: Communication, Clustering and Aggregation. *Ad Hoc Networks,* Volume 2, pp. 45-63.

Ni, L., 2008. *China's national research project on wireless sensor networks.* proceedings of the IEEE International Conference on Sensor Networks, p. 19.

Peng, Y., Qiao, W., Qu, L. & Wang, J., 2018. Sensor Fault Detection and Isolation for a Wireless Sensor Network-Based Remote Wind Turbine Sensor Network-Based Remote Wind Turbine. *IEEE Transactions on Industry Applications,* Volume 54, pp. 1072-1079.

Petersen, S. D. P. et al., 2008. A Survey of Wireless Technology for the oil and Gas Industry. *Proceedings of the SPE Intelligent Energy Conference.*

Prauzek, M. et al., 2018. Energy Harvesting Sources, Storage Devices and System Topologies for Environmental Wireless Sensor Networks: A Review. *Sensors,* 18 (2446), pp. 1 - 22.

Raza, M. et al., 2017. A critical analysis of research potential, challenges and future directives in industrial wireless sensor networks. *IEEE Communications Surveys and Tutorials*, pp. 1 - 61.

Ren, J. et al., 2005. an offshore safety assessment framework using fuzzy reasoning and evidential synthesis approaches. *Journal of Marine Engineering and Technology,* 4(1), pp. 3 - 16.

RMRI Plc., 2009. *Assessment of Risks Associated with the Alternator Rotor End Cap Disintegration on the Thistle Alpha Platform.* Manchester: Petrofac Facilities Management Ltd..

Saaty, T., 1980. *The Analytical Hierarchy Process.* NY: McGraw-Hill Book Co..

Saaty, T., 1990. How to Make a Decision: The Analytical Hierarchy Process. *Journal of Operational Research,* Volume 48, pp. 9-26.

Saaty, T., 1994. *Fundamentals of Decision Making.* Pittsburgh, PA: RWS Publication.

Sadeghi, A., Farhad, H., Moghaddam, A. M. & Qazizadeh, M. J., 2018. Identification of accident-prone sections in roadways with incomplete and uncertain inspection-based information: A distributed hazard index based on evidential reasoning approach. *Reliability Engineering & System Safety*, Volume 178, pp. 278 - 289.

Sarobin, M., 2020. Optimized Node Deployment in Wireless Sensor Network for Smart Grid Application. *Wireless Personal Communications,* Volume 111, pp. 1431-1451 https://doi.org/10.1007/s11277-019-06925-7.

Tang, L., Feng, S., Hao, J. & Zhao, X., 2015. Energy-efficient routing algorithm based on multiple criteria decision making for wireless sensor networks. *Wireless Personnal Communications,* Volume 80, pp. 97-115.

Wang, J., Yang, J. B. & Sen, P., 1995. Safety analysis and synthesis using fuzzy sets and evidential reasoning. *Reliability Engineering & System Safety,* 47(2), pp. 103 - 118.

Xiaojuan, C., Dargie, W. & Guan, L., 2009. *Energy Model for H2S Monitoring Wireless Sensor Network.*

Yang, J., 2001. Rule and Utility based evidential reasoning approach for multiattribute decision analysis under uncertainties. *European Journal of operational Research,* Issue 131, pp. 31 - 61.

Yang, J. B. & Xu, D. L., 2013. Evidential reasoning rule for evidence combination. *Artificial Intelligence,* Volume 203, pp. 1-29.

Yang, J. & Xu, D., 2002. On the Evidential Reasoning Algorithm for Multiple Attribute Decision analysis Under Uncertainty. *IEEE Transactions on Systems, Man and Cybernetics - Part A: Systems and Humans,* 32(3), pp. 289 - 304.

Yu, L. & Shrivastava, S., 2016. *Distributed Real Time Compressor Blade Health Monitoring System.* Annual Conference of the Prognostics and Health Management Society.

Zargar, O., 2014. Vibration analysis of a gas turbine: SIEMENS 162MW - v94.2 related to Iran power plant industry in Fars province. *Journal of Mechanical Design and Vibration,* 2(1).

Zhang, X., Gong, B., Yang, F. & Ang, S., 2019. A stochastic multicriteria acceptability analysis–evidential reasoning method for uncertain multiattribute decision-making problems. *Expert Systems*, 36(4), pp. 1 - 14.

Zio, E., 2018. The future of risk assessment. *Reliability Engineering & System Safety,* Volume 177, pp. 176 - 190.