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Wireless Vibration Data Collection Deployment in Offshore Oil & Gas Production Platforms in the Gulf of Mexico

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ABSTRACT: *Wireless vibration sensors are well suited for the remote locations of offshore production platforms in the Gulf of Mexico (GoM). By nature, they are not American Petroleum Institute (API) compliant due to their wireless connectivity and are solely advised for balance of plant (BOP) equipment, not critical equipment. There are many advantages of wireless technology ranging from logistics to lead time for data and its analysis. It is difficult to assess the benefit of the additional data available and quantify the data benefit of wireless vibration sensors on offshore oil and gas production platforms. This paper compares the data available from traditional route-based data collection with high-rate wireless vibration data collection. The benefits of wireless vibration sensors include improved logistics, extended datasets and expedited analysis with enhanced accuracy and anomaly detection.*
Keywords - *Vibration analysis, wireless technology, condition monitoring, condition based maintenance, offshore oil & gas, rotating equipment*

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I. INTRODUCTION

The outer continental shelf is a sizeable source of energy for the U.S., and over the past three decades, deepwater oil and gas production in the GoM has increased substantially (TRB, 2016). The federal government awards leases to oil and gas operating companies for production of resources under a sealed-bid auction process. The lease operators are responsible for exploration to discover new oil and gas resources, the development of discoveries, the subsequent production of oil and gas and the decommissioning and abandonment of depleted fields.

Offshore production is not only crucial to power automobiles and power plants but also environmentally preferable to drilling on land because offshore platforms emit far less greenhouse gas than production of the same amount of oil and gas on land (Penn, 2024). The greenhouse gas emissions associated with extracting a barrel of oil from the GoM are a third lower than emissions from producing a barrel of oil from fields on U.S. soil (Penn, 2024).

The offshore platform refers to the host facility for a producing field, whether dedicated to a single field and located near it or located some distance away. In both cases, that platform exercises operational control over the field (TRB, 2016). The first fixed production platforms were commissioned in deep water in the 1970s and the first floating platforms in the 1980s. Some upgrades have taken place, but many offshore facilities and legacy systems have not been or cannot be upgraded (TRB, 2015). Connecting onshore and offshore facilities has been driven by operators' desire to increase productivity, reduce costs, and share information in real time across multiple industrial and enterprise systems (Byres, 2012). As of 2016, there are forty-eight fixed platforms along the shore, three compliant tower and forty-six floaters at a water depth more than 400 ft (Kaiser & Liu, 2017).

The GoM has emerged as a critical hub for offshore oil production, significantly contributing to the U.S. economy and global energy markets. Deepwater production in the region increased from twelve million barrels annually in 1990 to more than four hundred million barrels in 2014 (TRB, 2016). In 2019, the offshore operators supported approximately 345 thousand jobs in the U.S. and contributed an estimated \$28.7 billion to the U.S. economy. Government revenues derived from offshore oil and natural gas operations, are projected to average over \$7 billion per year (NOIA, 2019). The basin is predicted to become the second largest producer of crude oil in the world after Brazil with daily output of 2.2 million barrels in 2030 (Ponnusamy, 2020). Currently GoM is considered to be the third-largest oil-producing basin in the world with over one million wells that have been drilled combining both deep and shallow water (Ponnusamy, 2020).

Operational resilience and technological innovation are critical for GoM operators facing both market volatility and environmental disruptions. Despite unstable oil prices, the GoM operators need to innovate continuously to grow to meet the demand of the global market as forecasted. GoM is well known for its tropical storms and hurricanes that regularly impact operations (Ponnusamy, 2020). The occurrence of hurricane season in the GoM is seasonal and occurs from June to November with the most active period falling between mid-August and mid-October (Kaiser, 2008). When needed, a platform shutdown takes place by closing the well heads and subsea valves operated by an automatic control system (Kaiser, 2008).

Due to the limited space and remote location of offshore operations, selecting cost-effective, efficient, and long-lasting equipment necessitates an elevated level of competence. The challenge for platform managers is balancing asset design, maintenance, and replacement costs with the costs to the oil and gas business in terms of finance, time, and resources throughout their life-cycle. There are more challenges with platforms in deep water locations such as high-water depths, harsh weather conditions, extreme wind conditions, and extreme wave heights emphasizing the need for risk assessments and facilities management (Amaechi et al., 2022). Risk assessments are carried out to ensure that the platform's risk level remains below acceptable levels over the operating life, and that it is as low as reasonably practicable (ALARP). The ALARP philosophy is common in the oil and gas industry. The offshore industry has adapted to technology and the digital age which has led to the reduction of skilled personnel within the industry due to automated processes (Amaechi et al., 2022).

Helicopter transportation has become an essential and increasingly relied-upon component of offshore oil and gas operations in U.S. waters. Over a five-year period, the Bureau of Safety and Environmental Enforcement (BSEE) estimates that 152.5 thousand helicopter trips are taken per year to support offshore oil and gas operations in U.S. waters (Upton et al., 2021). Data includes information on over 200,000 helicopter trips traveling over eleven million miles in a single year (Upton et al., 2021). This is an indicator of how crucial helicopter transportation has become in modern offshore production. As platforms move farther offshore, crew changes have increasingly been conducted by air rather than boat. With floating platforms commonly two hundred miles offshore, helicopter transportation is the logical option for the hundreds of engineers, operators, maintenance, and other workers who will produce the new finds (Zullo, 2019). Helicopters can carry five to eighteen passenger with costs ranging from $5,000 to $8,000 per flight. These costs vary by the size of helicopter and the distance travelled (Zullo, 2019). From a logistical standpoint, this level of air traffic requires precise coordination of flight schedules, crew rotations, and platform access to ensure operational continuity and safety. Planning teams must also account for weather disruptions, airspace regulations, and emergency response capabilities, all of which directly impact production timelines and cost efficiency. Given the high cost per flight, optimizing passenger loads and minimizing unnecessary trips is essential for budget control and resource allocation.

BSEE plays a critical role in enhancing offshore operational safety and environmental protection through regulatory oversight and the promotion of advanced technologies such as remote real-time monitoring (RRTM). BSEE is one of the federal agencies responsible for regulating the activities of the life cycle to promote safety and protect the environment (TRB, 2016). The offshore industry uses subsea development systems that allow a host platform to be miles from the producing wellheads on the seafloor, and a single platform can act as the host for a number of distinct fields spread over a large geographic area. The Outer Continental Shelf Lands Act mandates the use of Best Available Safest Technology (BAST) in offshore operations wherever practicable and economically feasible (TRB, 2016). The U.S. Department of the Interior advises BSEE on the use of RRTM to improve the safety and reduce the environmental risks of offshore oil and gas operations (TRB, 2016). The use of RRTM is variable across the offshore oil and gas industry. No industry standard for the implementation of RRTM exists, and the industry exhibits varying levels of maturity in its use of RRTM. Operators using RRTM realize benefits related to increased efficiency, reduced downtime and operational disruptions, reduced equipment damage, increased safety, and overall reduction in risk (TRB, 2016).

1.1 Condition Based Maintenance

Oil and gas production projects, are capital-intensive undertakings with financial and environmental consequences if they fail. Every year, industry in the U.S. spends approximately $200 billion on maintaining plant equipment and facilities while poor maintenance causes losses of up to $60 billion (Surucu et al., 2023). The three main maintenance strategies are corrective maintenance, periodic or calendar-based maintenance, and condition based maintenance (CBM). A combination of these methods are usually adopted to improve the availability of rotating equipment. Corrective maintenance is a reactive approach to maintenance in which corrective action is taken in post failure or upon detection of imminent failure (Moubray, 1997). Periodic maintenance is performed at predefined intervals, but often results in many unnecessary site visits and financial losses in practice. The third approach, CBM, involves continuously monitoring, where maintenance is based on the actual health conditions of the equipment (Yan, 2023).

CBM has emerged as a vital strategy for ensuring the safe, efficient, and reliable operation of offshore oil and gas platforms. In order to ensure that production continues in a safe and reliable manner, an efficient and effective maintenance program is essential. CBM is maintenance based on the measured condition of an asset (Bloch & Geitner, 2006). The ability to collect and manage data through integrated onshore facilities has allowed enhanced services to the industry (Booth, 2009). CBM, also known as predictive maintenance, is an approach to performing maintenance on the basis of the condition of a component as measured or predicted by diagnosing its state of health, detecting and isolating failure modes, and estimating the component's remaining useful life (TRB, 2016). CBM is critical to the efficient and safe operation of oil and gas platforms due to the complicated and integrated nature of offshore oil and gas facilities, detailed CBM plans with condition monitoring (CM) data collection and analysis, are required to offer information to determine maintenance intervals. As a result, more efficient equipment can be used with greater assurance and safety (Johnson et al., 2022).

CBM is currently utilized in the offshore oil and gas industry, with CM of wells resulting in incremental production advantages of up to 5%. Despite the large and complex equipment, facilities often employ limited personnel. In this case, an effective CBM approach ensures that condition data reaches the right personnel to assure that maintenance activities are concentrated in the areas demanded. The difficulties of inspecting offshore platforms in deep water accentuates the importance of CM practices (Johnson et al., 2022).

CBM is important to oil and gas companies' ability to maintain production levels as they move into increasingly harsh environments. Maintenance intervals are likely to differ from those in more amenable environments; the efficiency and effectiveness of maintenance support services and supply delivery may be impacted. This demonstrates the need for CM data understanding various maintenance intervals, Mean Time Between Failure (MTBF), and Mean Time Between Repair (MTBR), as well as providing longer lead times for maintenance and operations (Johnson et al., 2022).

CBM aims to identify a range of faults before they become critical to allow more accurate planning of corrective actions. CBM is based on the philosophy that maintenance should be carried out when it is needed. When maintenance is implemented based on calendar intervals, maintenance resources are often carried out resulting in costly efforts. Another risk of excessive maintenance is that maintenance situations may be created when maintenance goes wrong which can be costly if production has to be interrupted (Jantunen, 2014).

The evolution and institutionalization of CBM reflects a strategic shift toward leveraging technology for more efficient and effective maintenance. CBM was developed in the 1940s, but implementation was not widespread until the late 1990s due to the technological advancements of electronics and communication in the CM devices and communication of the information to the system analyst (Wiseman, 2006). The Department of Defense (DoD) has invested heavily in CBM. Their focus is to meet the warfighter expectations while conducting cost effective operations. In 2007, DoD established a policy for CBM+, which provides an integrated strategy for deployment of technologies, processes, and procedures that focus on a range of weapon system improvements. CBM+ was originally developed as a DoD initiative to focus on maintenance improvements that benefit both the maintainer and the warfighter (DoD, 2008). It was established to expand upon CBM and embrace other technologies, processes, and procedures that promote improved maintenance and logistics practices (Ali, 2022).

1.2 Condition Monitoring

CBM relies on data from CM to plan and schedule maintenance on assets. CM involves the use of technology to detect potential failures before they occur. CM consists of hundreds of techniques to detect potential failure effects such as a change in vibration, change in temperature, particles in lube oil, etc. (Moubray, 1997). CM assesses equipment health by analyzing parameters such as vibration, flow rate, indicated horsepower, motor amperage, temperatures, pressures, lubrication, and wear debris analysis (Townsend & Badar, 2018). Research has found that 99% of all machinery failures are preceded by some nonspecific malfunction sign (Bloch & Geitner, 2012).

CM is a well established technology and is used in the aeronautical and automobile industries (Serene & Chze, 2015). The motivation for introducing CM is to increase the safety level while decreasing the costs associated with maintenance which can be accomplished through increased reliability and reduced consequences of failures. The investments in CM equipment is normally offset by reduced production losses. The investment costs are recovered by reduction of maintenance cost and reduced costs of increased damage (Hamed et al., 2009).

The reliability of an asset is the probability that the item will perform a specified function under specified operational and environmental conditions, at and throughout a specified time. The formula is $R = e^{-\lambda t}$ where R is reliability, λ is the failure rate, and t is the time (Kales, 1998). Reliability is a key performance indicator often used to assess the effectiveness of a CBM program. The scope of CM is restricted by the implementation cost, either the cost of permanently installing sensors or of manual collection of vibration data using portable equipment (Taklo et al., 2008). In engineering systems, resilience is the ability to withstand disruptive events, both internal and external, without interruption in operation, and if it occurs, to recover completely and quickly (Duran et al., 2021). System-level availability reflects the relationship between the time a physical asset is available and the total or nominal time for operation. Availability is an important parameter linked to maintenance and its efficiency (Duran et al., 2021). Availability is the possibility that an asset is operating as intended when used under stated conditions. The formula is $A = MTBF \div (MTBF+MTTR)$ where A is availability, MTBF is mean time between failure and MTTR is mean time to repair (Durivage, 2015).

Offshore platforms use a wide range of balance of plant (BOP) rotating equipment in the extraction of oil and gas. Rolling element bearings are one of the most common mechanical components of rotating equipment. The failure of these components is the reason for 45% to 55% of machines breakdown (Behzad, 2021). In 1947 Lundberg and Palmgren published a report on the Dynamic Capacity of Rolling Bearings which is still the basis for rolling element bearing life calculations today. In 1952 they expanded their vision to produce the formula that remains at the heart of all of today's standard for bearing life which is known as the L10 or the point at which 10% of the bearings will fail. A bearing's basic fatigue life rating is calculated using the number of rotations which 90% of all bearings in a specific group achieve or exceed a calculated time without failure (i.e., probability of failure is 10%). The standardized formula, known as the L10 or catalogue method, is the conventional means of calculating a bearing's life (ISO, 2007). The parameters used are bearing load, rotational speed, dynamic load rating and bearing type. The result is the bearing fatigue life or L10 (NSK, n.d.). Adjustments such as steel quality, better designs, more accurate production methods and improved surface finishes all played a role in the L10 increase (Sibley, 2010).

1.3 Vibration Analysis

Vibration analysis is the technique of using vibration signatures from machines to assess their condition and identify potential faults before they become failures (Randall, 2011). The first studies on shocks and vibrations were carried out at the beginning of the 1930s to improve the behavior of buildings during earthquakes. Later, vibration tests on aircraft were developed in the 1940s to verify the resistance of parts and equipment prior to their first use. In aviation, automobiles, and other fields, the monitoring of vibration parameters is critically essential to the normal operation of key components of certain large-scale facilities and equipment. The real-time measurement of vibration parameters has become crucial for prolonging the life span and improving the reliability of the system (LI et al., 2021).

When it comes to common rotating equipment faults such as unbalanced forces, misalignment, incorrect lubrication of ball bearings, metal fatigue and cracks in welded parts can be prevented through condition monitoring, particularly vibration monitoring. Vibration monitoring is the CM technique most well suited to rotating equipment because of the substantial number of rotating components, which may have additional movement when problems occur. CM sensors that are permanently installed are appropriate for use in hazardous or inaccessible environments, as well as when pumps are submerged (Johnson et al., 2022).

1.4 Wireless Technology

Data collection is one of the most relevant topics of modern automation and industry. It is usually a costly and time-consuming task, especially in continuous processes, such as offshore oil and gas production. A CM tool is highly applicable, however given the number of data points, the cost of a commercial solution becomes unfeasible by many companies. Accurate and reliable data measurement and acquisition to predict failure events is the general goal of this approach. The quality of the anomaly predictions is highly dependent on the quality of the data.

The mechanical equipment condition monitoring system using wired connections is widely used in many large-scale equipment detection and process control systems. However, the traditional wired connection method has some shortcomings. The wired connection system requires additional connection cables, so the signal is susceptible to interference during transmission. If the transmission distance is long, the lengthy cable will cause problems such as increased installation cost and maintenance cost. In recent years, the development of wireless sensor networks has broken this wired connection model (Lei & Wu, 2020).

Most of the existing mature vibration monitoring systems on critical equipment use wired connections to connect sensors, signal conditioning equipment, and data acquisition equipment. This data acquisition method has many connections, complicated wiring, easy cable damage, high cost, poor maintainability, and disadvantages such as lack of flexibility. For rotating equipment, a wired connection is difficult to effectively complete the monitoring task (Niu, 2022). A wireless sensor network has easy deployment, flexible expansion, and easy maintenance. Using wireless sensor network nodes, the vibration measuring points can be networked so that the mechanical equipment and the monitoring system can be combined into a whole, constituting the Internet of Things system (Niu 2022).

Wireless technology users benefit from reducing the costs of hardwiring and maintaining sensor deployments, clearing safety and regulatory obstacles to running cables in constricted or dangerous areas, and improving operational visibility by detecting problems before they occur and create downtime losses (Hernandez et al., 2007). It is important to note that wireless technologies shall not be used for protective functions (API, 2021). As such, wireless technologies cannot be used to shutdown, or trip, rotating equipment. However, the technology is ideal to replace traditional route-based vibration data collection to provide alarm or alert functions.

The wireless sensor network monitoring mode is a novel technical method for acquiring vibration signals. It uses a large number of distributed sensor nodes to self-network to construct a wireless data transmission method, thereby making up for the traditional wired monitoring system in some special insufficient circumstances (Lei &

Wu, 2020). There is no shortage of competition in the wireless vibration analysis market as established vendors and newcomers continue to fight for market share resulting in benefits to the consumer. Users can select a system that integrates with their existing enterprise software to ensure continuity with personnel end users. A typical system consists of a gateway and tri-axial accelerometers that compile a mesh network that connects back to enterprise software across multiple platforms.

The deployment and performance of wireless sensor networks in offshore settings depend heavily on gateway placement, sensor mounting methods, and power management considerations. The number of required gateways depends on the distance between sensors, sensors locations and the line of sight between sensors. The gateway locations are selected looking to guarantee the best signal strength and attempting to reduce communication interference. A single gateway can accommodate up to two hundred sensors (Emerson, 2018). A wireless accelerometer battery life is approximately three years assuming ten-minute data collection intervals (Bently Nevada, 2021). The sensors can be mounted with studs, magnets, or epoxy. There are pros and cons to each mounting method which is a compromise between the ease of installation and the available frequency range of the data (Eshleman, 1999).

Automated alert systems and remote diagnostics play a critical role in streamlining maintenance workflows for offshore equipment. Alerts are established for specific equipment and notifications are sent via e-mail to an established personnel distribution list. Depending on the interconnectivity of the systems, the option to automatically create troubleshooting work orders in the computerized maintenance management system (CMMS) is an option. The data is remotely accessible by Subject Matter Experts (SME) to help diagnose problems and provide troubleshooting and corrective recommendations to remediate the detected anomaly. There are viewpoints that a senior level engineer or SME should review the data before work is assigned to offshore maintenance personnel.

1.5 Route Based versus Wireless Sampling

Offshore oil and gas production platforms have highly critical rotating equipment equipped with continuous vibration monitoring that includes established alarms and shutdowns tied to the main central control room. These systems have remote access capabilities available for SMEs to troubleshoot issues real time 24 hours per day. The BOP equipment is monitored by a traditional route-based vibration analysis program where a certified vibration analyst travels offshore once per quarter to collect and analyze data. There is a large assortment of BOP rotating equipment offshore that can benefit from condition monitoring such as vibration analysis. BOP equipment includes blowers, screw compressors, centrifugal pumps and compressors, positive displacement pumps and reciprocating compressors. Typical services include sea water, crude oil, methanol, air, and natural gas.

Traditional route based vibration data collection for offshore BOP rotating equipment presents significant logistical and environmental challenges that impact efficiency and data reliability. The traditional route-based data collection requires a technician to travel offshore to collect vibration data on BOP rotating equipment. The data is downloaded into software where various levels of alarms indicate the operating condition of the equipment into categories such as good, fair, slightly rough and rough (Rathbone, 1964). In vibration analysis systems equipment is referred to as machine trains. For example, a crude oil export pump that consists of a motor, gearbox and pump is one machine train. The simplest machine train would be a direct coupled configuration (i.e., motor and pump). A typical offshore platform in the GoM has approximately fifty BOP machine trains.

The access to the equipment can cause data collection time to vary. Ladders, stairs, scaffolding, confined spaces, and the distance between machine trains can add to the collection time. In addition, time is spent coordinating equipment swaps with operations to collect all data on the platform within a single visit. Environmental factors such as extreme heat, high wind and rain can increase the data collection time while the equipment's proximity to the edge of the platform heightens the technicians exposure to sea water and wind. Extreme conditions and limited time can impact the repeatability of the data based on measurement location. In addition, logistics are needed to coordinate technician availability to collect baseline data or perform troubleshooting which is dependent on helicopter flight availability and personnel on board (POB).

II. METHODOLOGY

The purpose of the study was to compare the quantity of data available between the traditional route-based data collection utilizing a certified vibration technician and permanently mounted wireless vibration sensors for BOP equipment. Quarterly route-based vibration data (velocity RMS) was collected from a simple machine train over a one-year period. The quarterly data from one measurement point was used to calculate the mean, standard deviation, Confidence Interval (CI), upper bound and lower bound. A Monte Carlo simulation was used to model the ten-minute wireless data collection interval over a one-year period. The Monte Carlo model was used to calculate the CI, upper bound and lower bound. Bell Curves were created for both data collection methodologies, quarterly route based and ten-minute wireless, to demonstrate the analytical benefits provided by the additional data available.

III. RESULTS

See figures 1 and 2 below for the bell curves of the quarterly and ten-minute data collection sample rates showing a single measurement location (i.e., pump outboard bearing horizontal) with a 99% CI over a one-year period. The quarterly bell curve shows the collected data (4 samples) while the ten-minute bell curve shows monte carlo data (52,560 samples). The bell curves demonstrate the additional data available from the wireless technology sample rates

Figure 1 - Quarterly Bell Curve

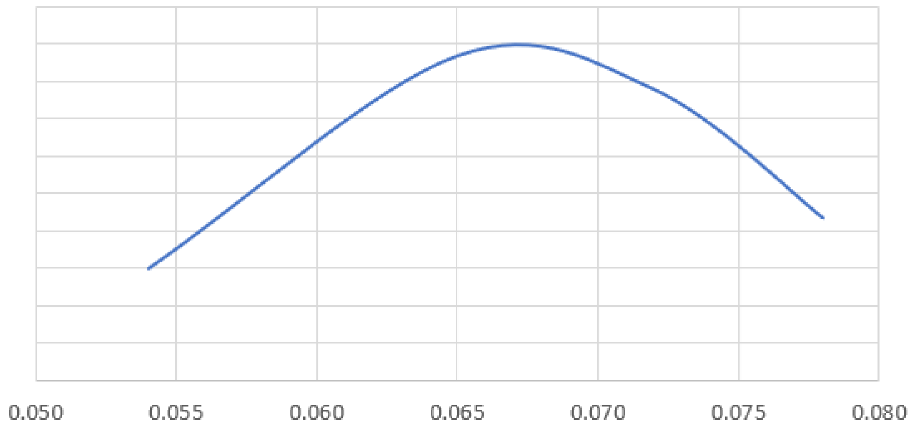
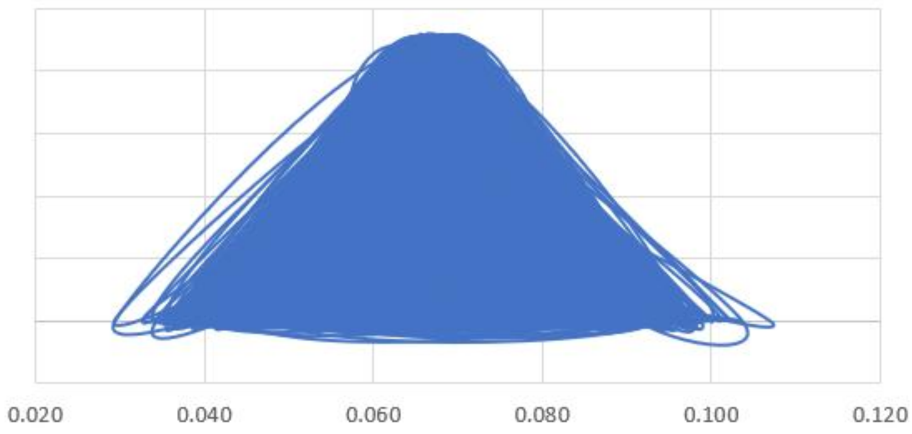


Figure 2 - Ten Minute Bell Curve



See table 1 below for a statistical comparison between the ten-minute and quarterly data collection frequencies. The table highlights the impact of the sample size on the CI. The smaller CI indicates a more precise estimate.

Table 1

Confidence Level	Sample Size (n)	Mean (μ)	Std Dev (σ)	Confidence Interval (CI)	Upper CI	Lower CI
99%	4	0.06725	0.008927	0.011497	0.078747	0.055753
99%	52,560	0.06725	0.008927	0.000100	0.067350	0.067150
95%	4	0.06725	0.008927	0.008748	0.075998	0.058502
95%	52,560	0.06725	0.008927	0.000076	0.067326	0.067174
90%	4	0.06725	0.008927	0.007342	0.074592	0.059908
90%	52,560	0.06725	0.008927	0.000064	0.067314	0.067186

In a basic machine train configuration, vibration data is collected from multiple bearings to monitor system performance. A simple machine train would consist of four bearings, two in the motor (driver) and two in the pump (driven). There would be a total of twelve data points in the machine train; horizontal, vertical, and axial measured at each bearing.

More data leads to more accurate estimates and alarm parameters. Analyzing small sample sizes, confidence intervals are wide, indicating high uncertainty. Analyzing larger data sets, intervals are narrow, improving certainty. When there are very few data points, rare events might be missed entirely, biasing the result. Larger datasets are more likely to capture those rare but important failure modes. More data increases statistical results, making it easier to detect true defects. It is important to recognize the downside of a higher confidence level is a wider interval, therefore the higher the desired degree of confidence, the longer the resulting interval. The only 100% CI for a mean is infinite upper and lowers bounds, which is not useful, as even before sampling, we know this interval covers the mean. The length of the interval can be thought of as specifying its precision, the confidence level, or reliability, of the interval is inversely related to its precision.

Simply examining the quantity of data available to analyze fifty simple machine trains shows a 13,139% increase in data with the wireless sensors for data collection when compared to the traditional route-based data collection. The standard error (SE) is the estimated measure of variability in the sample distribution. The SE decreases as the sample size increases. As expected, the wireless collection SE is lower than the traditional route-based sampling. See table 2 below for a SE comparison between the ten minute and quarterly data collection. The table demonstrates the sample size impact on the SE.

Table 2

Collection Method	Sample Size (n)	Std Dev (σ)	Std Error (SE)
Route Based	4	0.008927	0.004464
Wireless	52,560	0.008927	0.000039

A typical equipment configuration is three by fifty percent, meaning that two assets are in operation while one is in standby. This configuration allows for maintenance, with one pump down, operations are left with a single point of failure but can still complete maintenance on the out of service pump. Splitting the standby time between the three assets means that each machine train will accumulate 5,840 hours per year. A typical rolling element bearing life (L10) is approximately 40,000 hours. Staggered run life and failures creates different remaining useful life (RUL) between components within machine trains and between machine trains. This adds complexity to vibration analysis because all equipment has unique components which makes RUL difficult to use as a decision method for maintenance work. Vibration data does not necessarily follow the bearing RUL as operating conditions and environment play a role in how the equipment operates. See table 3 below for vibration and bearing life comparison for the quarterly data collection. The table highlights that the vibration level does not coincide with the RUL.

Table 3

Time (hours)	Vibration (in/sec RMS)	Predicted RUL (hours)	Bearing Life (L10)
1,460	0.072	38,540	96.35%
2,920	0.078	37,080	92.70%
4,380	0.054	35,620	89.05%
5,840	0.065	34,160	85.40%

IV. CONCLUSION

There are many benefits to installing wireless vibration sensors on BOP rotating equipment on offshore production platforms in the GoM. The technology allows engineers to have access to 24-hour per day surveillance, more data is available to trend and analyze, and it allows for immediate baseline data after repairs. In addition, the wireless sensors eliminate missed data collection that occurs with traditional route-based data collection that requires personnel support for swapping equipment. The wireless technology removes time delay for offshore travel to troubleshoot, eliminates labor hours, reduces POB, reduces helicopter flights, and reduces safety risks from manual data collection.

The wireless systems require the upfront costs of purchasing equipment such as wireless sensors, gateways, and software along with the installation and commissioning. Some operators already have a traditional route-based program in place that has been proven to be effective and will require economic justification to change to wireless technology. See table 4 below for a comparison between ten minute and quarterly data sample rates.

The table demonstrates the superiority of the higher sample rates and the impact to the reliability and availability of BOP rotating equipment.

Table 4

Aspect	10 Minute Samples	Quarterly Samples
Granularity	High resolution: captures short-term variations	Extremely course: misses fluctuations
Trend Detection	Can identify trends, cycles and anomalies	May miss short-term trends or noise
Responsiveness	Enables real-time or near-real-time decisions	Only supports long-term planning
Forecasting Accuracy	Better model training for time series	Poor input for predictive models
Anomaly Detection	Spot outliers, spikes, and drops	Anomalies are averaged out or hidden

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