Contract T8009-210079/001/XLV

P1.9 Report on Relationships Between Noise, Vibration, and URN Measurements

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Un sommaire français se trouve avant la table des matières

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Executive Summary

This report presents the findings of measurement and analysis activities surrounding underwater radiated noise generated by the Queen of Oak Bay Ferry. The project aimed to quantify the relationship between measurements of noise and vibration made on board the ferry, and the underwater radiated noise signature measured external to the vessel, as well as to advance the underpinning technology (Allsalt Maritime's Kinetix vibration measurement system) to a pre-commercial state and demonstrate that it can successfully predict underwater radiated noise levels.

The project took a multi-phase data collection approach which aimed to establish and trial suitable noise and vibration sensor deployment arrangements, before building on those sensors by including hydrophone measurements. This spanned five separate phases, including a trial phase, two phases with on-board sensors only, and two phases with hydrophones.

Prior to commencing measurement activities, an Exploratory Data Analysis (EDA) was conducted on an existing dataset from internal Queen of Oak Bay sensors. Results from this showed strong correlations between engine power, fuel consumption, water column depth, and speed through the water. The additional observation was made that the data obtained in the EDA was likely to be difficult to correlate with sensor data, as each data point covers a period of one minute, as either an average or a maximum value.

The first deployment phase occurred between October 13th and October 30th, 2021, with eight Kinetix vibration and six Tascam noise sensors installed at key locations on the Queen of Oak Bay ferry: at main engine and gearbox positions in the central machinery space, at a position along the prop shaft at both ends of the ferry, and in the steering gear compartments located below the main car deck. Vibration measurements spanned the entire duration of this install period, whilst noise measurements were limited to the first three days of the installation, owing to battery constraints. Initial review of the data from this measurement period showed that sensors were recording correctly, and the data was intelligible as machinery-space data, confirming the methodology for future deployments. The remaining on-board sensor only data collection phases were conducted in the same manner, with some minor changes to the installation location required. Some sensor locations were also revised during Rounds 1 and 2 due to damage to cabling or exposure to excessive quantities of engine oil.

The two hydrophone data collection phases occurred between December 13th 2021 and January 7th 2022. In each of these two phases, on board data was collected as per the previous sections, but a one-day hydrophone deployment was conducted at the start of each of the Round 3 and Round 4 phases. Round 3 hydrophone data was collected at a location close to the Queen of Oak Bay's berth at Horseshoe Bay and Departure Bay on December 13th and 14th 2021 respectively. There were some practical issues with the hydrophone deployment during Round 3 which resulted in some measurement periods where the hydrophone was out of contact with the water. This was fixed for the Round 4 data collection. During the Round 4 data collection period, one hydrophone was deployed at a fixed location (Departure Bay), whilst a second hydrophone was deployed from the Allsalt Maritime trials boat to capture eight crossings of the Queen of Oak Bay over the course of single day on January 5th, 2022.

The results from all four phases of data collection were examined for consistency and integrity, and down selected to enable processing. This data review showed that the hydrophone data gathered at the stationary measurement positions from rounds 3 and 4 were not practical for use in further analysis, as there were too many confounding factors, such as multiple vessels being in dock at once and the presence of nearby small craft, and they have been excluded from further analysis. This was a known risk as obtaining useable hydrophone measurements in shallow water close to a dock presents a number of challenges and unknowns. Mitigation of this risk was part of the reasoning for the deployment of a hydrophone from the Allsalt Maritime trials boat to provide a second measurement location during the final phase.

The final analysis was performed on the subset of data for which there was both good hydrophone data and good data from on board sensors. This corresponds to the seven pass-by events recorded in the final data collection phase. This data was first processed to convert it from a time history of the physical characteristics of the signals to a power spectral density (PSD) which shows the frequency and energy content of the corresponding time history signal, with each PSD covering a period of 10 s, resulting in a total of 420 individual PSD records. A peak-finding algorithm was then applied to each PSD record, which extracted the frequency and magnitude at which a tonal component of the overall noise signal was observed, as well as the width of the tone, and its prominence (i.e. the amplitude of the peak relative to the amplitude of the PSD surrounding it). All four of these parameters were fed forward into the machine learning portion of the project.

Machine learning techniques were used to predict the peaks in energy in the PSD of the underwater radiated noise measured via hydrophone remote from the vessel from the on-board machinery vibration measurements. Two approaches were examined, based on their known capacity for working with this kind of data: a Neural Network approach, and a Random Forest approach. Strong correlations between the URN signal and the machinery vibration signals measured at the End 1 main engine were found with both machine learning approaches, where the accuracy of prediction is 84.8% with the use of Neural Net and 89.52% with the Random Forest method.

This project demonstrated that it is feasible to use on board measurements of machinery vibration to predict key components of the underwater radiated noise away from the ferry via the application of machine learning tools. Future work in this sphere should consider additional data collection periods to strengthen this prediction and look to provide a framework for developing this prediction to represent broadband noise levels that fit more readily with legislative compliance.

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Glossary of Terms

Term	Definition
DLB	Digital logbook, Kinetix component which logs and stores data
g	A standard unit of acceleration, equivalent to 9.81 ms^{-2}
Kinetix	Vibration sensor system produced by Allsalt Maritime Ltd.
k-means++	An unsupervised learning method that helps to group records of a dataset into k classes
Narrowband analysis	Method of signal analysis which looks at individual frequency components of a signal
Neural Network	A series of algorithms widely used in classification and endeavors to recognize underlying relationships in a dataset
PSD	Power Spectral Density, a measure of energy in a signal as a function of frequency
Random Forest	A supervised learning algorithm, which is known to perform well on a range of predictive model problems
RMS	Root-mean-square
SPU	System processing unit, accelerometer component of Kinetix
SSE	Sum square of errors
Tascam	Logging unit for airborne noise measurements
URN	Underwater Radiated Noise, general term for noise measured in water

1. Introduction

Allsalt Maritime has partnered with BC Ferries to instrument the Queen of Oak Bay with sensors to evaluate the feasibility of predicting Underwater Radiated Noise (URN) through on-board machinery vibration measurements using Kinetix. Kinetix is a vessel impact monitoring system currently deployed on small fast boats globally. Through previous research, it has been proven that Kinetix can accurately detect propellor cavitation on small vessels and alert the operator of its presence. The overarching goal of this project is to expand on the research to include larger ships and consider all sources of URN instead of cavitation specifically.

The objectives of this project are as follows:

1. Measure the relationships between URN and ship operating efficiency by correlating ship sensor data (including thrust, fuel efficiency, RPM, speed, and ship location) with hydrophone data and accelerometer data collected on Kinetix.
2. Quantify the relationship between URN and the above measurements so that URN can be directly estimated by dry onboard measurements.
3. Advance the Kinetix technology to a pre-commercialized state as a stand-alone onboard URN monitoring system for ships. At this stage of development, this could be paired with Allsalt Maritime's consulting services to deliver post-operational URN emissions reports.
4. Advance the Kinetix technology to a state where integration into ship bridge systems would be feasible, allowing development of real-time URN notifications to ship crews while the vessel is underway.

2. Activities and Deliverables

The project may be broadly considered to comprise three broad themes. To aid the reader, these themes are listed in Table 2.1 by where in the report they are covered.

Table 2.1 – Report deliverables and supporting evidence.

Deliverable	**Supporting Evidence**
Data capture and analysis	Section 3 - Summary of Project Activities Section 4 – Signal Processing Overview Section 5 – Application of Machine Learning
Build relationship between onboard measurements and URN.	Section 5 – Application of Machine Learning Section 6 – URN Prediction Accuracy
Assess the feasibility of predicting URN through on-board machinery vibrational and acoustic measurements	Section 5 – Application of Machine Learning Section 6 – URN Prediction Accuracy

3. Description of the Queen of Oak Bay

All measurements recorded during this project were taken from the Queen of Oak Bay, a double-ended C-class Ferry operating between Nanaimo and Vancouver. Double-ended ferries are designed so that vehicles can be loaded/unloaded from both ends without the need for the ferry to turn. It achieves this by having propulsion systems at both the nominal “bow” and “stern” locations. To facilitate this, machinery spaces are effectively mirrored about the middle of the vessel and the two ends are numbered to distinguish between them. For example, there is both an “End 1” and “End 2” main engine, propeller shaft, gear box, steering gear compartment etc.

The Queen of Oak Bay typically makes between four and five transits a day during peak operations, sharing duties with other vessels of the same class. It is 139 m in length, has a displacement of around 7000 tons (unloaded), and its typical cruise speed is around 35 knots. The Queen of Oak bay can be seen in Figure 3-1.

Figure 3-1 - Queen of Oak Bay underway

4. Summary of Project Activities

The scope of the project covers several rounds of instrumentation deployment and analysis, with complexity and duration of both aspects increasing as the project advanced. To provide the reader with the full context of this project, a summary of each phase is given in the subheadings below, with activities split into procurement and analysis aspects.

4.1. Exploratory Data Analysis

Prior to any measurements with Kinetix, Allsalt acquired a subset of the existing vessel monitoring data and conducted an Exploratory Data Analysis (EDA) to better understand existing relationships in the sensor data. The goal of the EDA was to find correlations between vessel parameters that are currently being measured.

This section includes information about the Queen of Oak Bay ferry dataset, a descriptive analysis to explain what the features are representing, and an investigation to identify relationships among the vessel's parameters.

4.1.1. Data Source and Description

The ferry machinery system parameters and environmental measures are collected through several sensors and stored as daily files using the IVY® Propulsion Performance Management tool. The historical dataset is acquired directly from the Queen of Oak Bay database.

This analysis utilized data collected throughout February 2021 comprising of 28 CSV files. Each CSV file corresponds to one day, and includes 1440 minute-average records and the following features:

- Date and Time Stamp
- Fuel Consumption
- Fuel Flowmeter
- Temp. at Flow
- GPS Speed Over Ground
- GPS Date & Time
- Vessel Position
- Speed Through Water
- Speed On Ground
- Ship's Heading
- Windspeed
- Wind angle
- Water Depth
- Torque
- Speed
- Power
- Thrust

4.1.2. Data Quality

The Queen of Oak Bay is a double-ended vessel with one propulsion system existing at either end for a total of two propulsion systems. However, one of the sensors had a disconnected line resulting in an incomplete propulsion data set for the End 2 main engine location.

This vessel uses a dual power control system, meaning it varies propeller pitch and engine speed to maximize efficiency. Varying propeller pitch changes the "advance ratio" of the propeller. This ratio determines the amount of water that a propeller displaces per revolution which impacts speed and efficiency. Unfortunately, the pitch measurements were not available in the dataset meaning this EDA disregards the effect of variable pitch on speed. This limitation has been communicated with BC Ferries to see if it can be addressed for the future analysis.

4.1.3. Descriptive Analysis

The aim of this project is to explore the relationship between URN and on-board machinery vibration measurements. Considering the goal of the project and to reduce the complexity in the visualizations, only the vessel's key operating parameters such as speed, power, and fuel consumption were selected for analysis. Some environmental variables like wind speed and wind angle have been reserved for future study.

- **ts**: Date and Time Stamp, data is obtained per minute
- **engine1**: Fuel consumption for engine 1, measured in (kg/h).
- **engine2**: Fuel consumption for engine 2, measured in (kg/h).
- **speedlog_stw_longitudinal**: Speed through water, measured in knots (kn).
- **gps_latitude**: Latitude of ship location, measured in (deg).
- **gps_longitude**: Longitude of ship location, measured in (deg).
- **speed1**: Shaft Speed for engine 1, measured in (rpm).
- **power1**: Shaft Power for engine 1, measured in (kW).
- **windspeed**: Wind speed, measured in knots (kn).
- **windangle**: Wind direction, measured in (deg).
- **depth**: Water depth, defined as the vertical distance between the lowest part of the ship's hull and the seabed, measured in (m).

As shown in Figure 4.3.1, ferry trips took place between 49.1 and 49.4 deg latitude and 124.0 to -123.2 deg longitude. This corresponds to the route between Horseshoe Bay to Departure Bay (Nanaimo) as seen in Figure 4-1 and Figure 4-2.

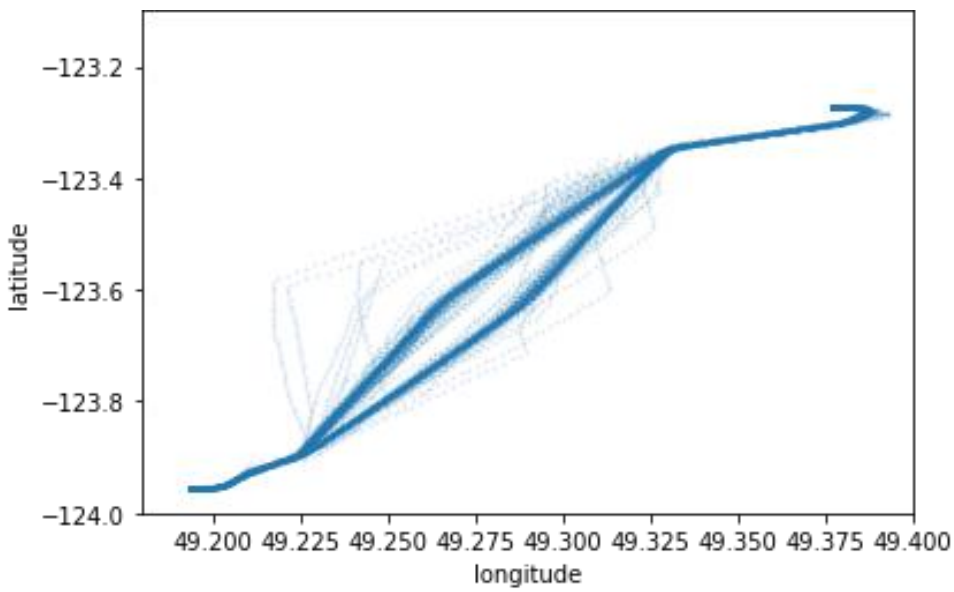

Figure 4-1 – Distribution of ferry location.

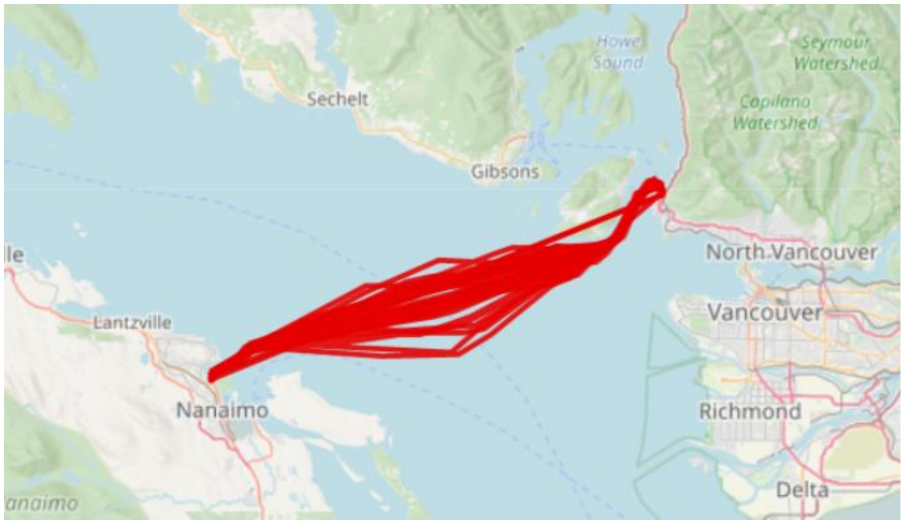

Figure 4-2 – Map overlay showing the ferry GPS locations.

Figure 4-3 shows the distribution of fuel consumption measurements in the data set. Density on the y-axis shows the percentage of all measurements which were recorded at the x-axis value (for example, the peak in the orange trace at around 300 kg/h shows that this value was observed in about 0.4% of all measurements observed. It can be seen from this the fuel consumption distribution for engine 1 and engine 2 are very smilar. As many measurements related to engine 2 are missing in the dataset, this observation implies that the result of analysis on engine 1 might be generalizable to engine 2.

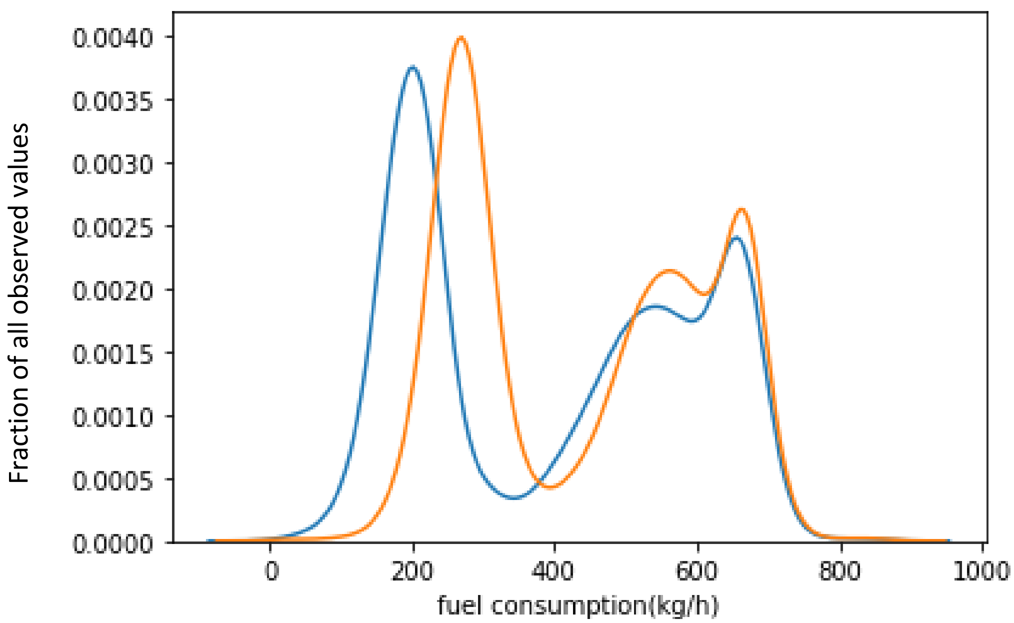

Figure 4-3 – Distribution of fuel consumption.

The distributions of the other features over their ranges are displayed as histograms in Figure 4-4.

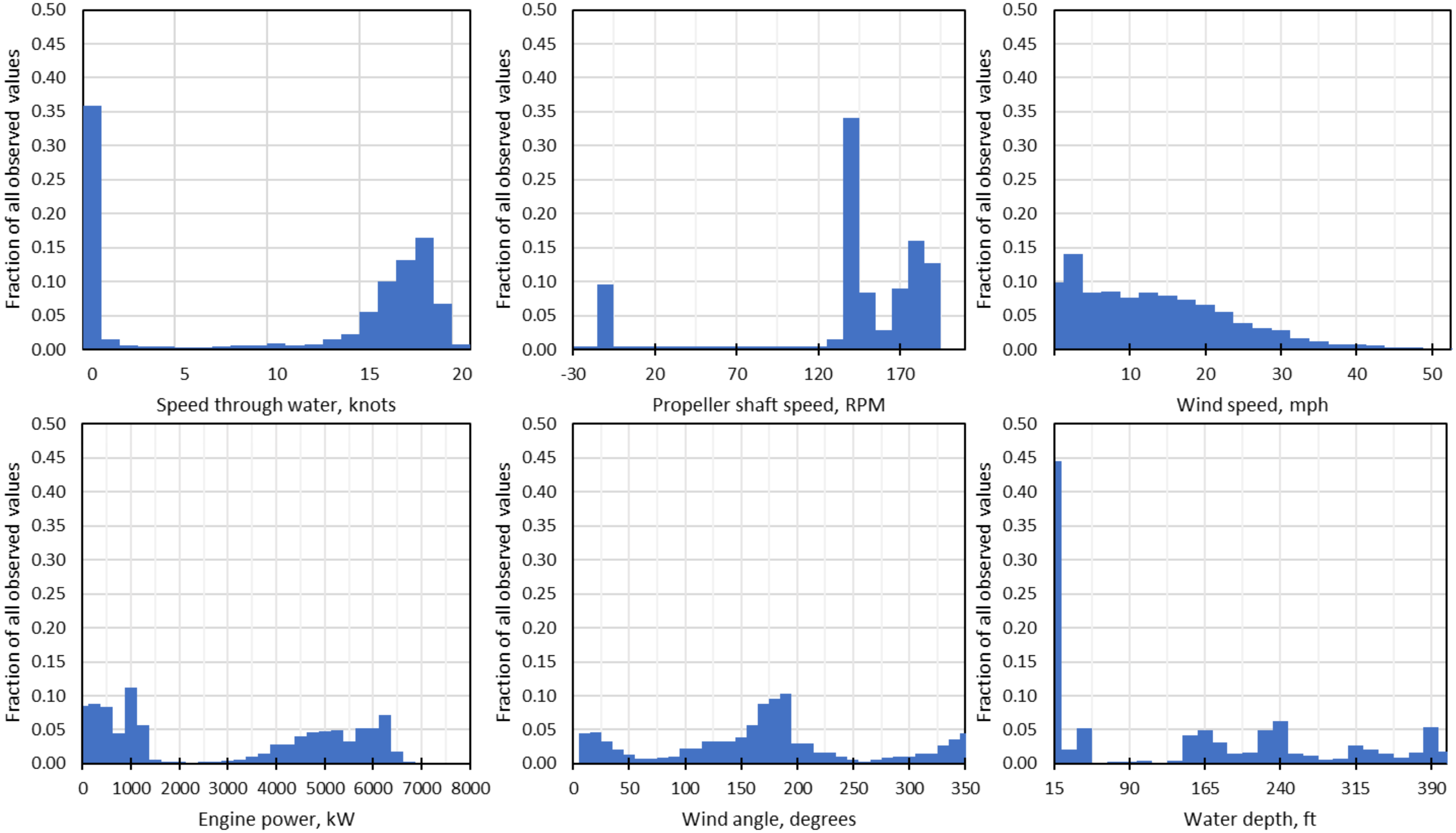

Figure 4-4 – Histograms of other features (from left to right starting at the top): speed through water, propeller shaft speed for engine1, wind speed, Engine 1 power generated, wind angle, and water depth.

4.1.4. Data Outliers

Some of the readings for fuel consumption and shaft power were zero or very close to zero, so it was decided to cleanse the data by removing these extremely low measurements. The effect of this data cleansing on the fuel consumption feature is illustrated in Figure 4-5.

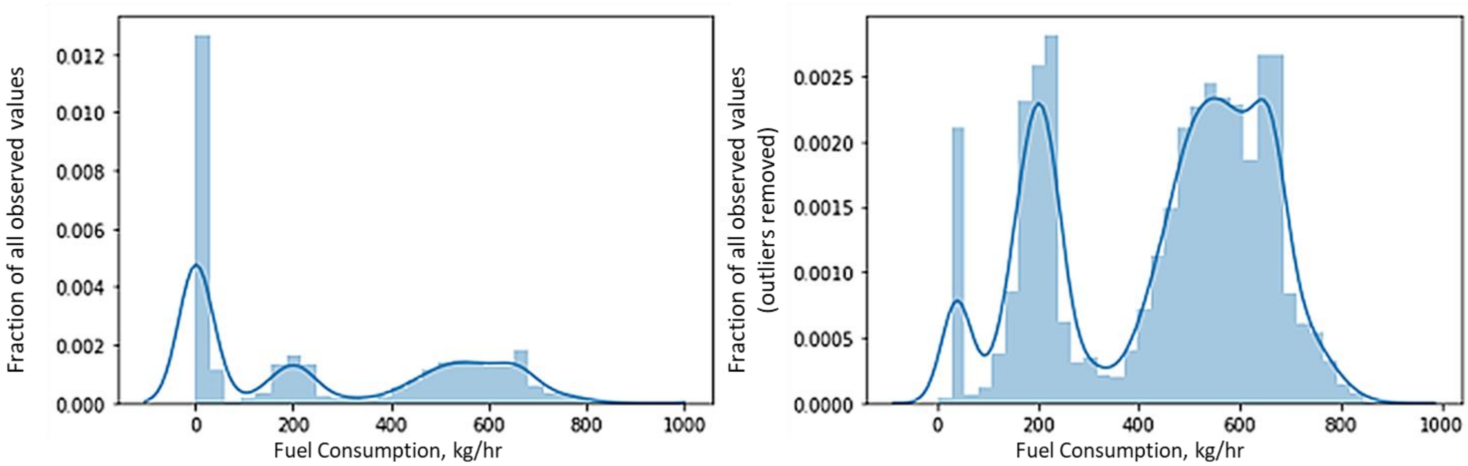

Figure 4-5 - Distribution of fuel consumption with and without outliers

There were a few negative entries recorded for the shaft speed feature. These entries are not correlated with vessel movements (latitude and longitude), and their magnitudes are not in the expected range and a clockwise/anti-clockwise operating fashion cannot be assumed. These entries most likely are related to sensor offset. Therefore, data filters were applied to exclude them.

As shown in Figure 4-6, some observations for shaft speed, windspeed, and wind angle are still numerically distant from the rest of the data. However, it does not mean they are necessarily outliers. These points for shaft speed might correspond to the engine warming up prior to operations, and for wind angle and wind speed they could represent unusual environmental scenarios. For these reasons they were reserved for further consideration.

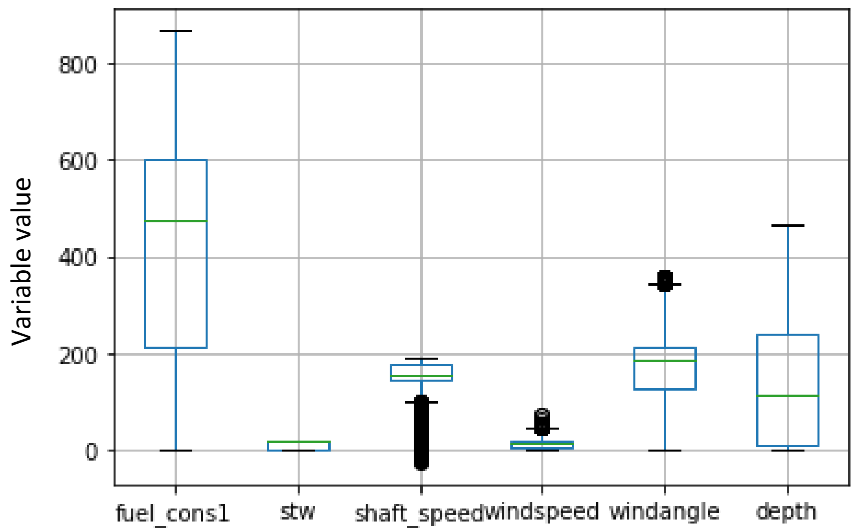

Figure 4-6 - Boxplot illustrating the outlier discovery.

4.1.5. Feature Correlation

Without having the dependent variable measurements (i.e. URN measurements using hydrophones), the correlation coefficients between all the selected features are shown and considered in Figure 4-7 and Figure 4-8. Only the features that are correlated with URN are of interest to this project.

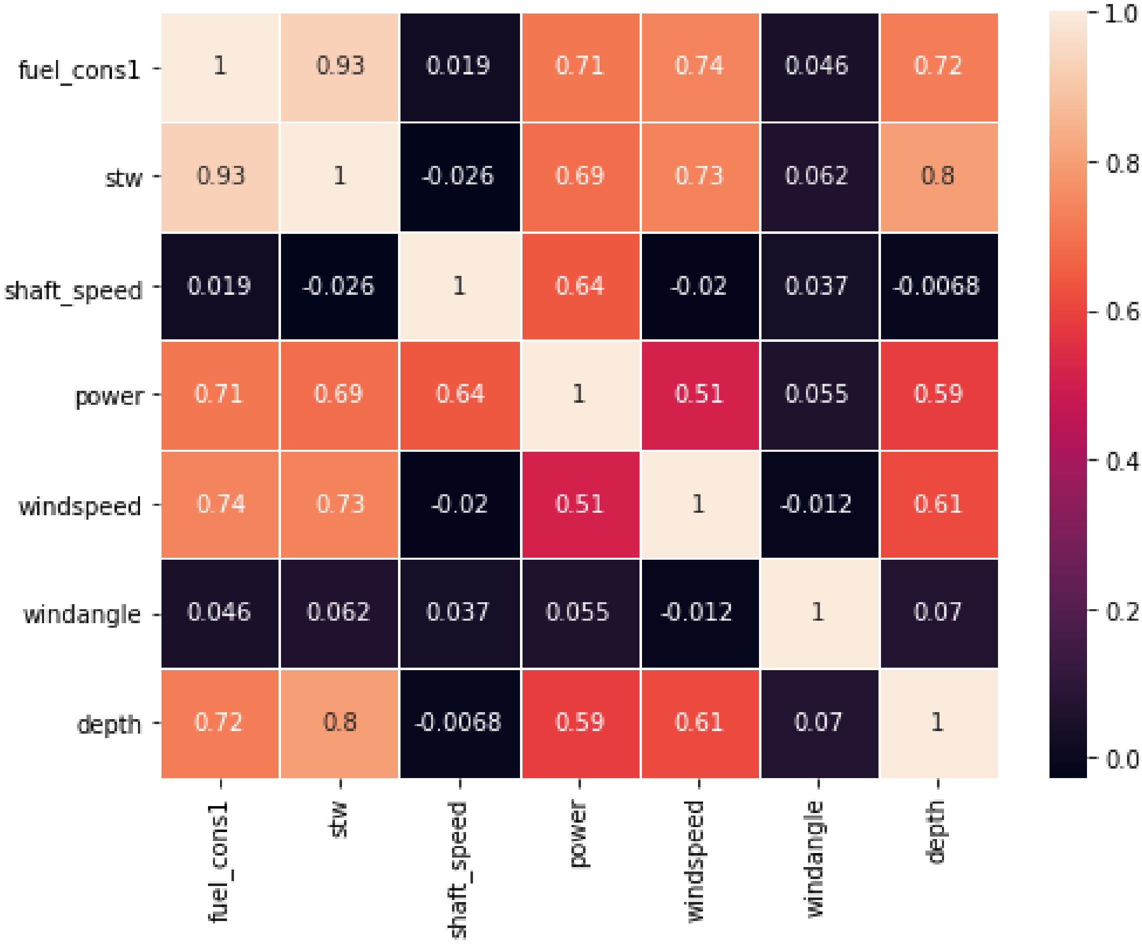

Figure 4-7 - Correlation matrix heatmap summarizing the data.

From Figure 4-7, it can be observed that fuel consumption and speed through water (stw) are highly correlated. It means if these features are correlated to the output variable, one of them can be excluded from the analysis. The assumption for many machine learning algorithms is that the independent variables need to be uncorrelated to each other to prevent a biased analysis. This means fuel consumption, stw, power, and shaft speed cannot be used together based on the correlation coefficients. The model performance metric can be used here to evaluate feature performance to decide which of the features need to be kept. Figure 4-8 represents the same data lay out as Figure 4-7 but with scatter plots instead of correlation coefficients.

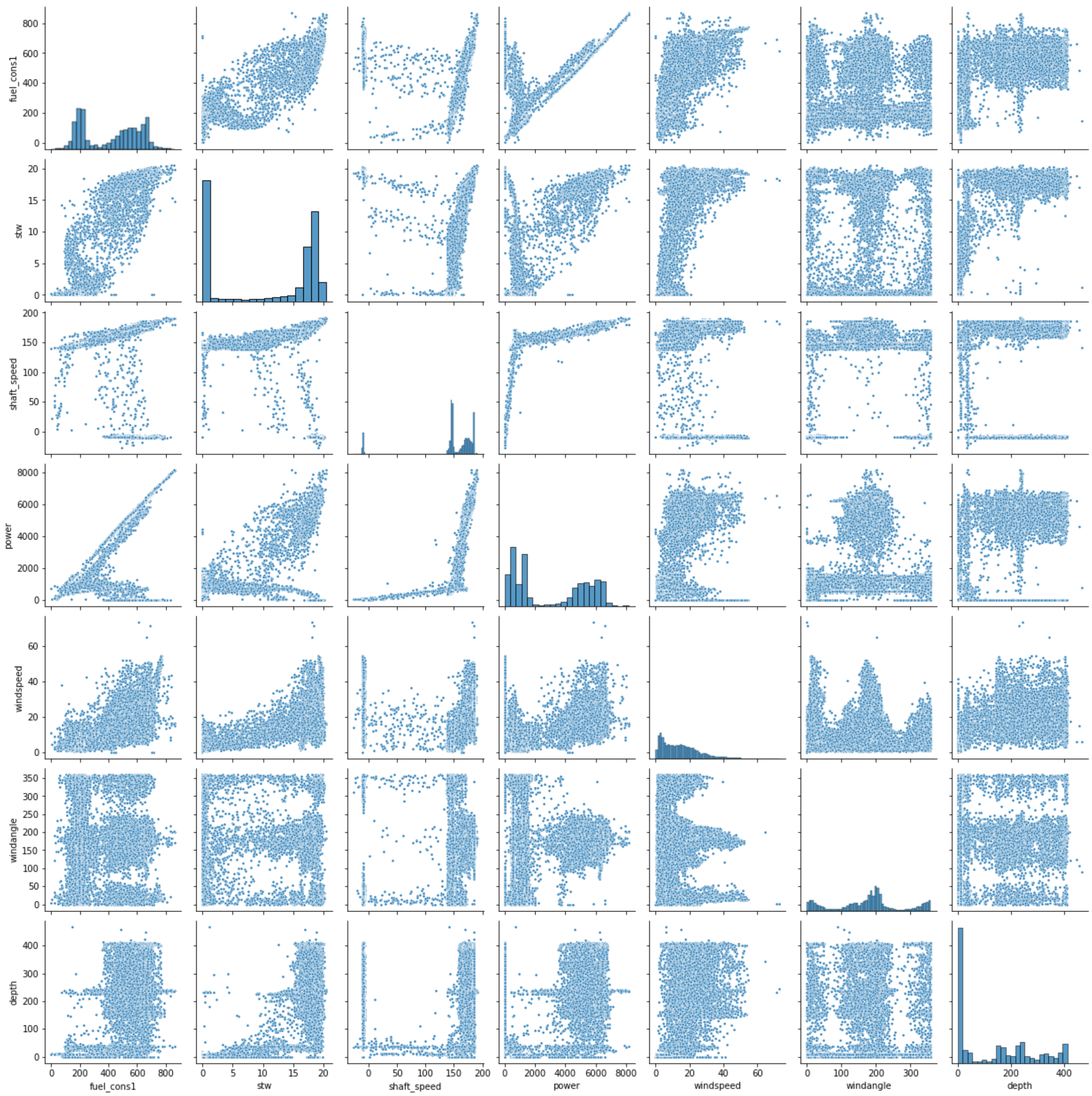

Figure 4-8 - Scatter plots summarizing feature relationships.

4.2. Data Acquisition Activities

The following sections give a summary overview of the process and progress of the installation of project-related measurement sensors.

4.2.1. Sensor details

The following subsections give an overview of the types and configuration of sensors used in the Queen of Oak Bay project. Details pertaining to their installation during each phase of the project will be given in Section 4.2.2 forwards.

4.2.1.1. Kinetix Vibration Sensor

The Kinetix vibration sensor system comprises three parts: the data logbook (DLB), the system processing unit (SPU), and the deck acceleration unit (DAU). These components are shown in Figure 4-9. The system is capable of recording vibration at two locations simultaneously, as the DAU and SPU both contain tri-axial accelerometers (i.e., accelerometers which can measure acceleration in vertical and two orthogonal horizontal directions). The maximum sample rate of the system is 1 kHz in a range of ±30 g with a resolution of 0.001 g[1], and the maximum sample rate setting was used for the Queen of Oak Bay installation.

The system can run on both internal battery and external power supply, with the external power supply being the principal mode of operation on Queen of Oak Bay, with the internal battery acting as a backup in case of loss of power.

The Kinetix system is capable of logging continuously (power depending) for up to 2000 hours (just under 12 weeks) using internal storage.

[1] ‘g’ is a common engineering unit for acceleration, equal to 9.81 ms^{-2}

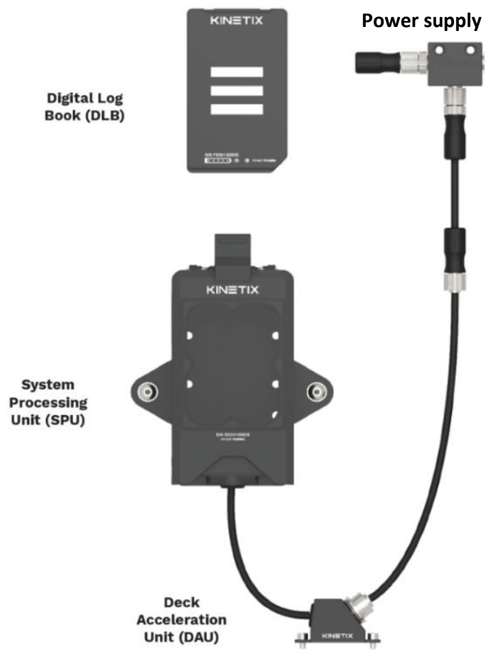

Figure 4-9 - Kinetix vibration sensor system. The DLB stores the data and is easily removed from the system. The SPU and DAU contain the two tri-axial accelerometers and the power supply (4) provides power to the system.

4.2.1.2. TASCAM/Countryman Noise Sensor

The noise measurement solution for the Queen of Oak Bay installation was to record the raw time history using a high-capacity recorder (the TASCAM DR-10C) and a robust omni-directional microphone (Countryman B3 omnidirectional microphone). Both components are shown in Figure 4-10.

The TASCAM DR-10C is a portable, battery-operated audio recorder, configurable to run at a variety of sensitivities and data quality configurations. It is also capable of running on external power, and an external battery pack solution was used to extend the operating duration of the noise sensor system.

The TASCAM DR-10C is capable of recording at a variety of sample rates, but to balance data quality and data storage requirements, its sample rate was set to 48kHz with a 24bit resolution. Because the system was intended for operation in machinery spaces, which may experience noise levels of more than 100 dB whilst underway, the system sensitivity was set to “Low”, which gives the maximum dynamic range for the system. Internal storage is limited by the operating system to 32 GB, resulting in a maximum theoretical run time of approximately three days.

The Countryman B3 Omnidirectional lavalier microphone is a small, low-gain, omnidirectional microphone with a nominally flat frequency response in the nominal human range of hearing (20 Hz – 20 kHz). These microphones were selected based on their robustness and low nominal sensitivity (4 mV/Pa), enabling them to cope with the high dynamic range expected from the environments in which they were installed.

Figure 4-10 - TASCAM DR-10C (left) and Countryman B3 (right)

4.2.1.3. OceanSonics icListen HF Hydrophone

The OceanSonics icListen hydrophone system is a self-contained underwater noise measurement system deployable in two different configurations: in an “attended” format with an external power source or using limited internal power, and in an “unattended” format, where the system is deployed with an accompanying “launch box” which contains additional power, storage, and a data link for real time data monitoring. The full system, including launch box, is shown in Figure 4-11.

Figure 4-11 - icListen hydrophone unit (left) and launch box (right)

The system was deployed in the Queen of Oak Bay project in both configurations, with measurements taken at static locations close to the ferry terminals using the launch box, and from the Allsalt Maritime trials boat using it’s attended configuration.

The system itself is configurable in several ways: its sampling frequency can be set from 16 to 512 kHz, and its resolution set to either 24 or 16 bits, resulting in a range of between 82 and 2 days of continuous recording using the internal 256 GB storage. For both deployment styles, the 24-bit, 128 kHz configuration was selected to give a balance of frequency resolution and ease of data processing (high sample rates correlate with high data processing time).

4.2.2. Test Installation of On-Board Sensor Systems

The objectives of the first mobilization to the Queen of Oak Bay, which happened in October 2021, were as follows:

- Confirm suitability of installation locations with regards to power sources for long-term running of measurement apparatus.
- Confirm suitability of installation locations w/r to data quality and potential insights, particularly with respect to potential overloading of sensors in machinery and engine spaces.
- Generate initial data set for creating data export and processing routines.
- Generate initial findings

Eight installation locations were identified prior to mobilization through conversation with BC Ferries, and are given in Table 4.1, with approximate locations shown graphically in Figure 4-12, Figure 4-13, and Figure 4-14.

Table 4.1 – Intended sensor install locations

Ref.	Description	Ref.	Description
1a	No. 2 end steering gear compartment	3a	No. 1 end engine mount
1b	No. 1 end steering gear compartment	3b	No. 2 end engine mount
2a	No 2. end propeller shaft	4a	No. 1 end gearbox
2b	No. 1 end propeller shaft	4b	No. 2 end gearbox

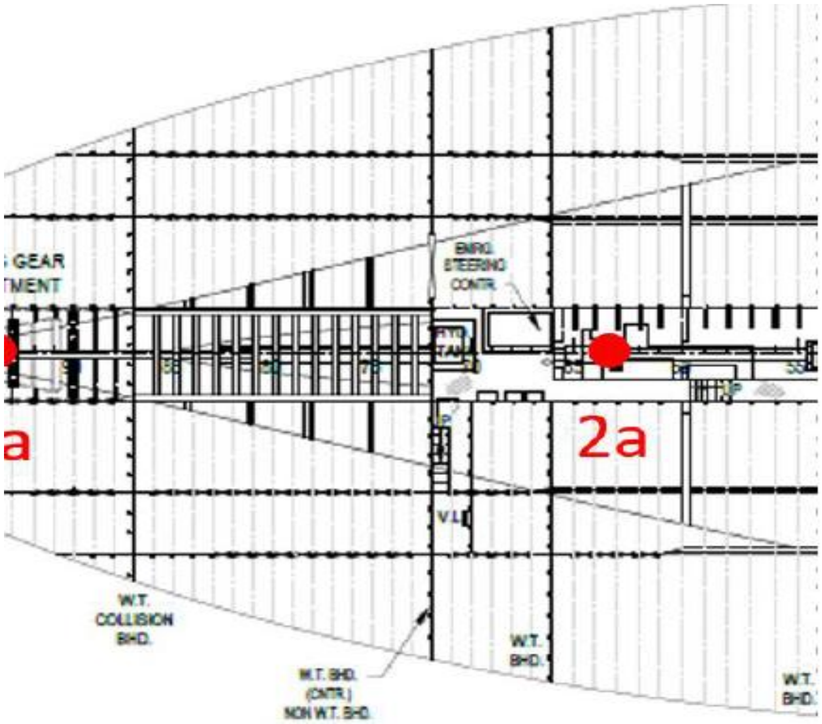

Figure 4-12 - No. 2 end sensor locations

Figure 4-13 – Engine space sensor location

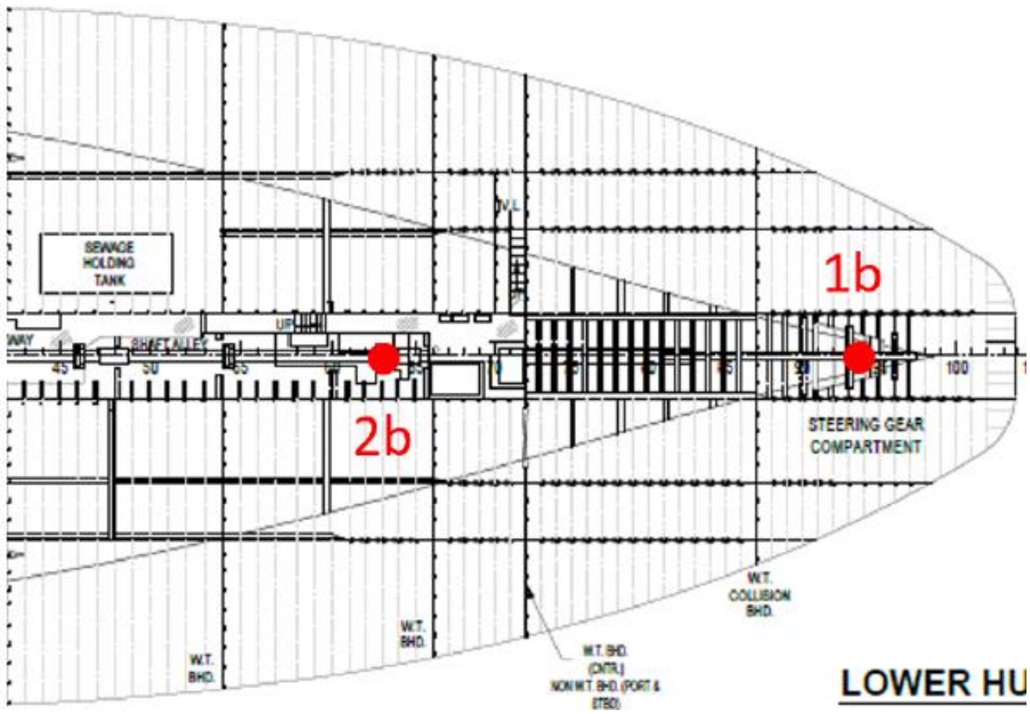

Figure 4-14 - No. 2 end sensor locations

Each sensor location comprised a pair of sensors, one for acceleration, and one for noise, resulting in a total of 16 sensors being installed on this first visit, as detailed in Section 4.2.1.

However, upon arriving at site, Allsalt technicians were met with several challenges that limited the spaces in which sensors could be installed and the total number of sensors installed in the main engine space being reduced. The principal difficulties related to the use of external power supply battery packs for the TASCAM systems. Use of off-the-shelf power supplies had been planned, but these were found to unpredictably switch to a standby mode due to the low power draw of the Tascam recorders, so a bespoke solution was manufactured at short notice in-house. Unfortunately, there was limited time for comprehensive testing ahead of the trial leading to issues with two power supplies on initial deployment. However, upon arriving at the install location, it became apparent that the difference in noise profile between the intended locations for noise sensors in the engine space would be minimal: it is a large, diffuse space with machinery producing high noise levels and many reflective surfaces, and therefore the noise level could reasonably be expected to be similar for measurement locations 3a, 3b, 4a, and 4b.

Additionally, it proved impractical to mount the Kinetix sensor at the end one gearbox because of insufficient access. It was decided that installation close to the gearbox would be sufficient, and the Kinetix sensor was instead installed at the rigid collar of a nearby boiler. An updated schematic of the sensor install locations in the main engine space is given in Figure 4-15, and example installation photos are given in Figure 4-16.

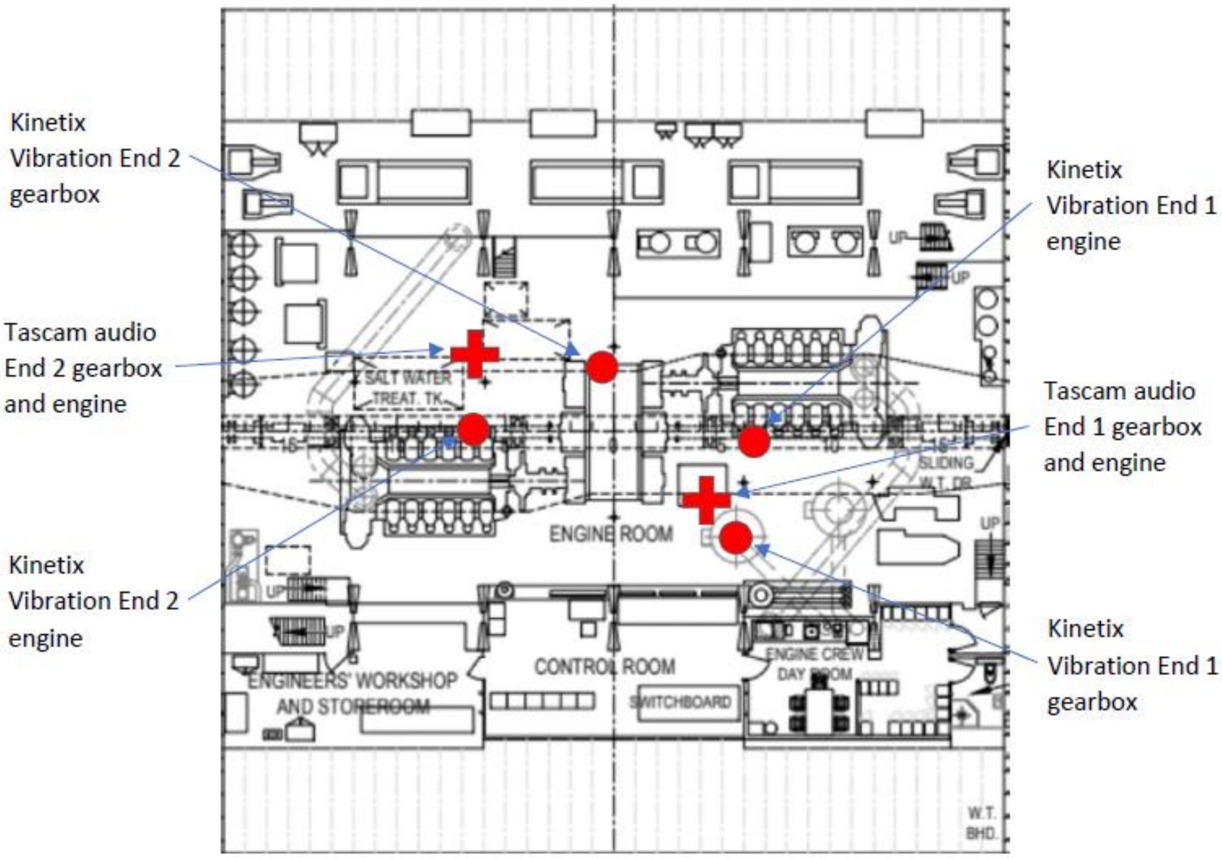

Figure 4-15 - Engine room sensor mounting locations. Kinetix systems identified by a red dot, TASCAM systems identified by a red cross

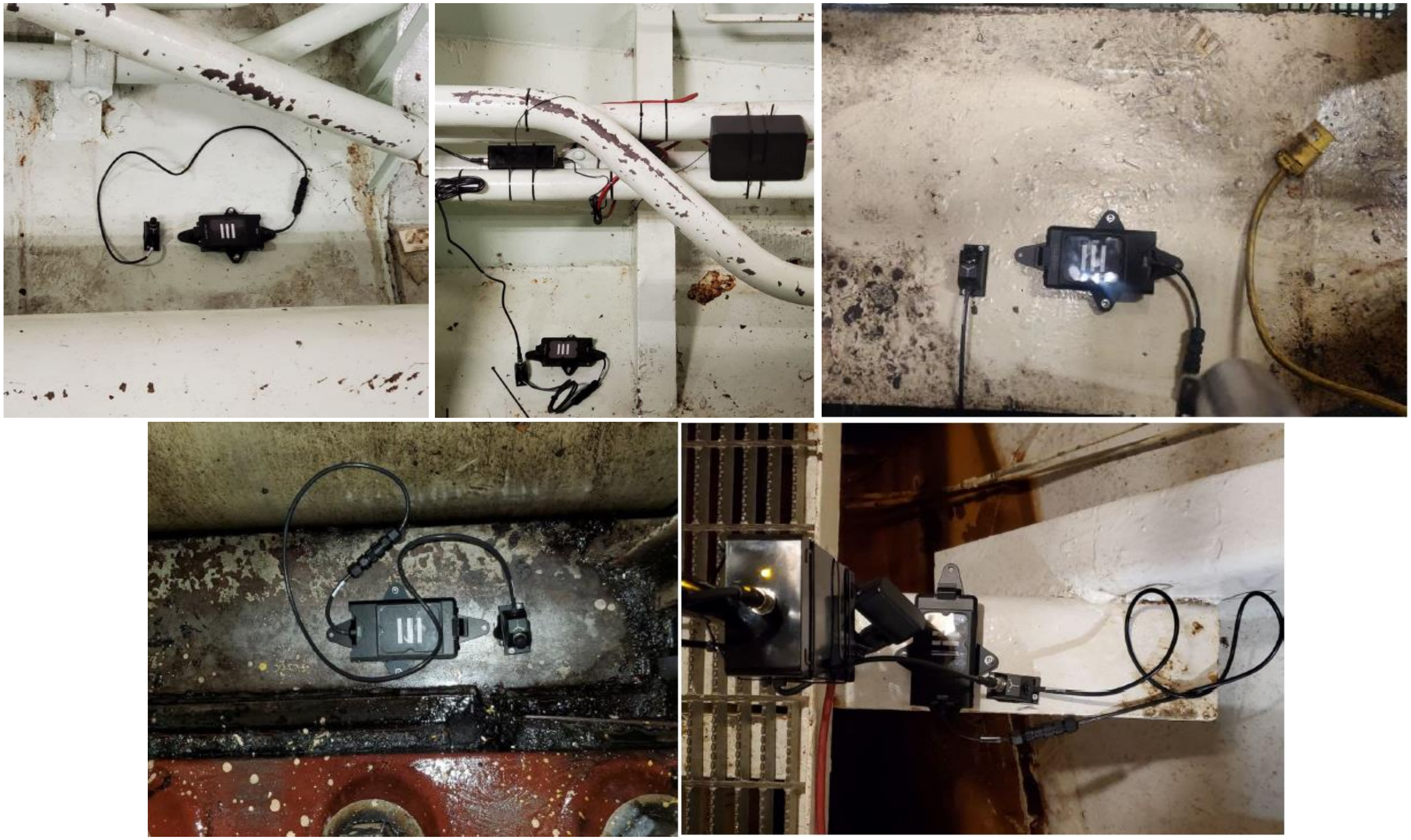

Figure 4-16 - Example sensor placement. Top left: Kinetix vibration sensor, End 2 propeller shaft; Top middle: Kinetix vibration and Tascam noise sensor, End 1 propellor shaft; Top right: Kinetix vibration sensor, End 2 gearbox; bottom left: Kinetix vibration sensor, End 1 engine; bottom right: Kinetix vibration sensor, End 2 steering compartment.

Results from this test installation were collected after approximately two weeks. To minimize future installation efforts, equipment was left in place whilst the Tascam memory cards were replaced, and the Kinetix data was downloaded over USB connection.

Initial review of the data showed a power failure in the End 2 gearbox location that was determined to be the result of ship side power coming unplugged from the unit.

All other sensors operated as expected. The schedule of which sensors were operating at what point during this phase is given in Figure 4-17.

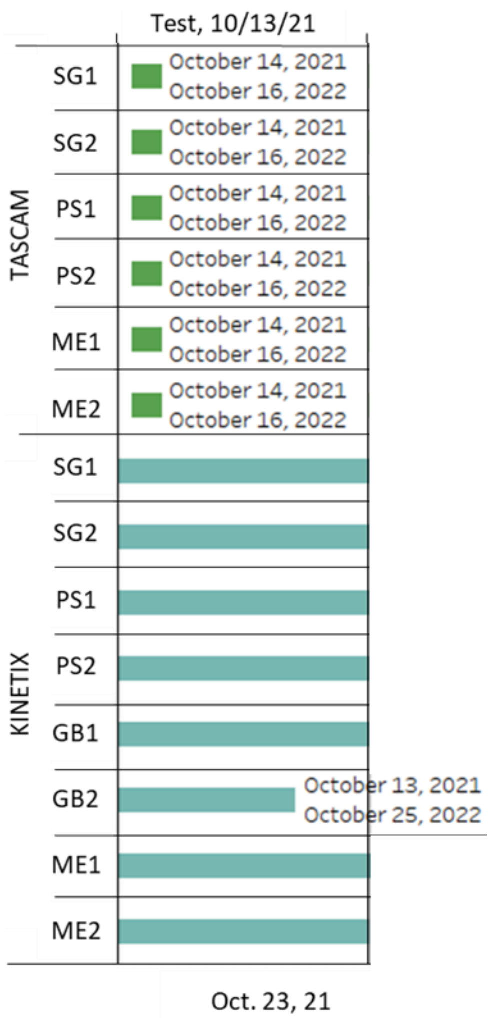

Figure 4-17 - Sensor up-time schedule, test deployment phase

The sensor up-time format is used in the following sections, and the key for the sensor-location shorthand is given in Table 4.2.

Table 4.2 – Glossary of sensor locations

Shorthand	Description
ER	"En route" measurements, pertaining to the hydrophone measurements made
HB	"Horseshoe Bay", the terminal hydrophone deployment location on the Vancouver end of Queen of Oak Bay's route
NN	"Nanaimo", the terminal hydrophone deployment location on the Nanaimo end of Queen of Oak Bay's route
SG1	"Steering Gear", pertaining to the Kinetix and TASCAM systems installed in the steering gear compartments located towards the front of end no.1 of the Queen of Oak Bay.
SG2	"Steering Gear", pertaining to the Kinetix and TASCAM systems installed in the steering gear compartments located towards the front of end no.2 of the Queen of Oak Bay.
PS1	"Propeller Shaft", pertaining to the point towards the propeller end of the propeller shaft at end no.1 of the Queen of Oak Bay at which the TASCAM and Kinetix systems are installed
PS2	"Propeller Shaft", pertaining to the point towards the propeller end of the propeller shaft at end no.2 of the Queen of Oak Bay at which the TASCAM and Kinetix systems are installed
ME1	"Main Engine", pertaining to the measurement location directly next to the number 1 engine
ME2	"Main Engine", pertaining to the measurement location directly next to the number 2 engine
GB1	"Gearbox", pertaining to the measurement location close to the gearboxes close to the number 1 engine
GB2	"Gearbox", pertaining to the measurement location close to the gearboxes close to the number 2 engine

4.2.3. Data Processing for Test Installation

The purpose of the test installation carried out in October 2021 was to stress test the equipment and to derive a data sample that could be used to check the measurement settings and determine whether there was evidence of clipping, data outages, etc.

Initial review of the data showed that all but one sensor operated for its theoretical recording time, limited either by battery life in the case of the Tascam systems, or memory in the case of the Kinetix system. The exception to this was the Kinetix sensor, which was installed on the End 2 gearbox, which was running on internal power after its connection to shipside power was broken, likely because of the high levels of vibration or because of crew access knocking it loose.

Data integrity was assessed by taking an indicative sample of 20% of the resultant files produced by each Tascam and Kinetix sensor set, and performing a visual inspection of the time histories, power spectral densities (PSD) and magnitude histograms.

Review of the time histories allows us to check for breaks in the data, which would be shown by discontinuities in the trace, and allow for a general check that what is being recorded seems to be indicative of the expected noise and vibration environment. An example acceleration trace, taken from the End 1 gearbox location, is given in Figure 4-18.

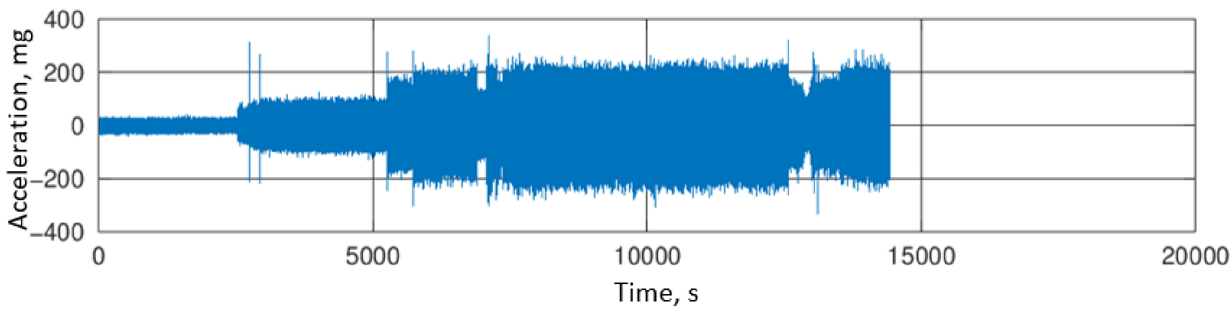

Figure 4-18 - Example acceleration time history trace from Gearbox 1

Review of the PSD figures gives an indication as to whether what is being shown on the trace is a realistic indicator of the expected operating profile (i.e. it would allow us to see clear engine or other machinery tones, where an incorrectly functioning sensor would not provide us with a clear indication of these). An example PSD trace for vibration measured at the End 1 engine location is given in Figure 4-19, with clear tones and broadband noise shown in the 80 – 120 Hz range, coincident with expected main engine firing rates etc.

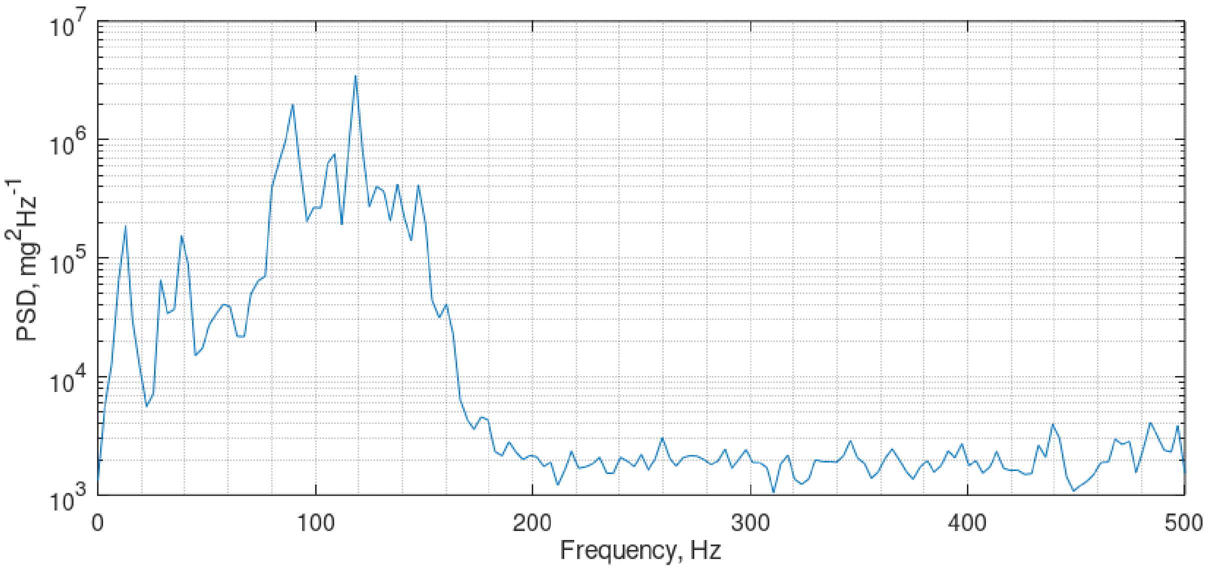

Figure 4-19 - Example PSD for End 1 main engine vibration measurement

Magnitude histograms are a useful indicator of where a sensor is being subjected to signals above its maximum capacity to sense. This is known as peaking and is observable in a time history event by a high magnitude event which is a flat line at the top of the peak coincident with the maximum possible output of the sensor. By normalizing the magnitude of a time history by the maximum value observed in the measurement period, you create an array of "fractions of maximum possible magnitude", which can then be plotted as a histogram. In a signal where peaking occurs, there will be a high incidence of "+1" and "-1" amplitude entries, allowing us to perform a quick visual inspection for evidence of peaking. An example histogram is given in Figure 4-20.

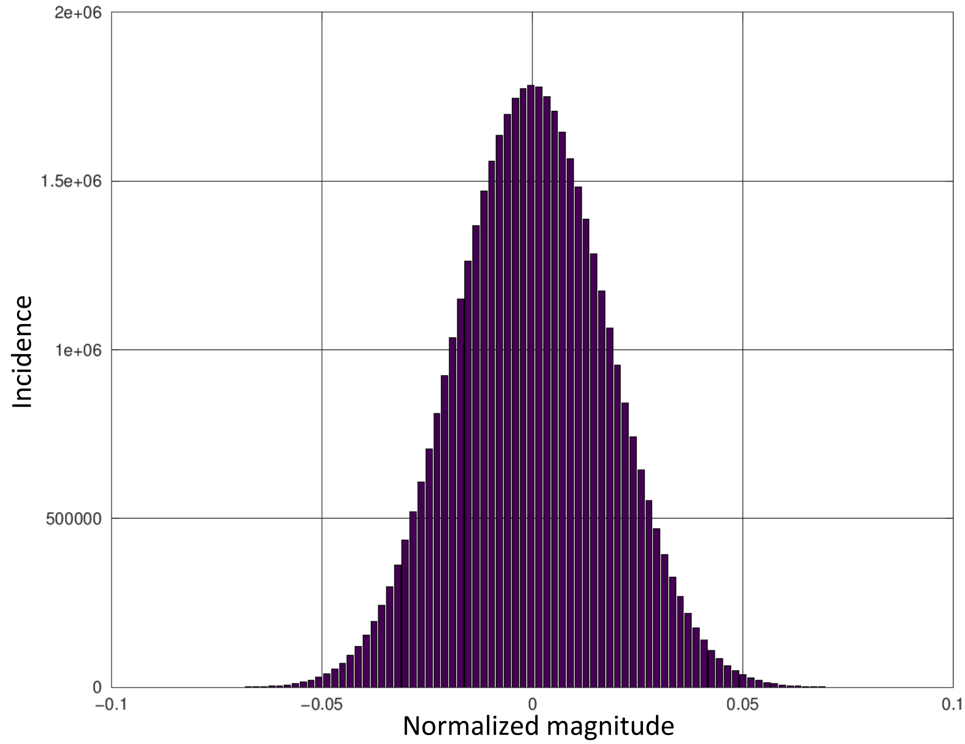

Figure 4-20 - Example normalized magnitude histogram for End 1 main engine Tascam sensor

This sample assessment using these three criteria showed:

- No obvious indicators that any sensor was subject to intermittent measurement issues, as indicated by the sample time histories
- Good correlation with expected frequency content for machinery spaces, as indicated by the sample PSD traces
- No evidence of any sensor in any location peaking, as shown by the normalized histograms.

4.2.4. Round 1 Data Collection

Round 1 data collection took place immediately following the test installation and covers the period October 30th to November 22nd, 2021. No substantial change in deployment was made to any of the installed sensors, and all sensors remained in the same location for this data collection period.

During this round of data collection, all the Tascam noise sensors concluded their theoretical maximum measurement period without incident.

Three Kinetix system failures were observed during this measurement period. The first at the End 2 gearbox measurement location, the second at the End 2 main engine location, and the third at the End 1 main engine location.

The End 2 gearbox recording error was observed to be the result of the power supply becoming disconnected from the system. It was determined that excessive vibration was causing power plugs to shake loose so cable ties were used to secure power supplies ahead of the next phase of data collection.

In the case of the End 2 main engine location, the failure was deemed to be the result of a faulty DLB in the system, or damage to the DLB resulting from ingress of oil into the system during installation or through the water-tight seal. The DLB unit was exchanged with a new unit prior to the commencement of the next phase of data collection.

The sensor uptime schedule for Round 1 data collection is given in Figure 4-21

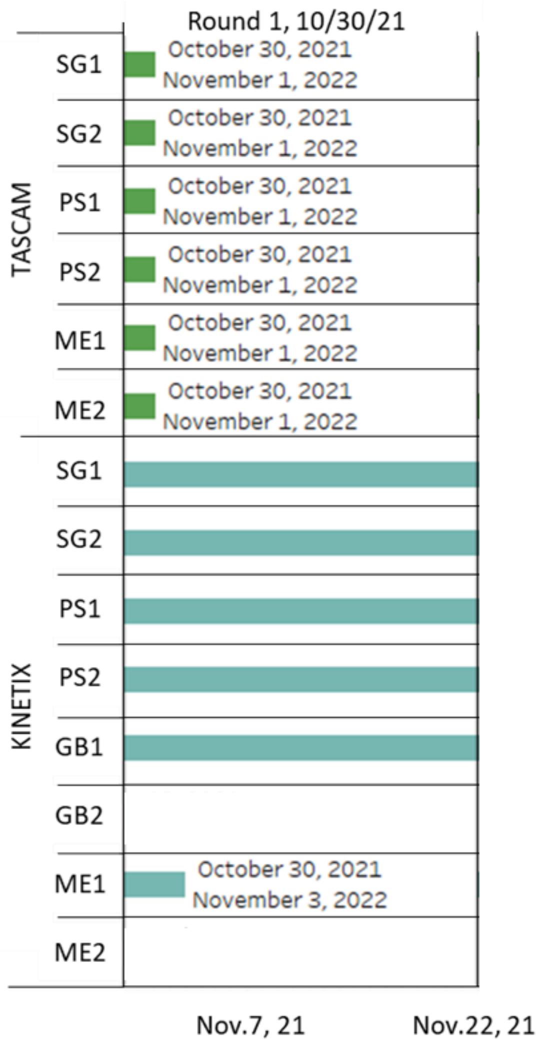

Figure 4-21 - Sensor up-time schedule, Round one data collection

4.2.5. Round 2 Data Collection

Round 2 data collection took place immediately following the test installation and covers the period November 22nd and December 13th, 2021. For this deployment, the sensors mounted at the base of the End 1 and End 2 engines

During this round of data collection, all the Tascam noise sensors concluded their theoretical maximum measurement period without incident at all but one location. At the End 1 main engine location, the sensor stopped recording after less than one day of operation due to a power supply issue.

Two Kinetix system failures were observed during this data collection period: End 2 gearbox, which recorded no data, and the End 2 steering gear location. Both of these failures were observed to be the result of damage to the power connections, and additional steps were taken here to secure the power supplies and reduce the likelihood of future issues of this kind.

The End 1 main engine fault continuation is the result of ingress of significant engine oil/lubricant into the system during the previous deployment, which had resulted in corrosion of the metal pins which connect the DLB to the other elements of the Kinetix systems. Examples of the damage experienced by this unit are given in Figure 4-22.

Figure 4-22 - Example corrosion on Kinetix SPU housing. Left, close-up of damage to pin housing causing loss of contact with DLB, right: oil sheen inside SPU housing

Two actions were taken as a response to this: firstly, the faulty unit was swapped out with a new unit, and secondly, the units at both main engines were reposition such that they were no longer sat in pooling oil/lubricant from the engines themselves, with the DAU – where oil ingress is not a concern – mounted in the same location. The new SPU mounting location is shown in Figure 4-23, with it mounted to the nearby walkway rather than to a mounting plate down in the engine support skid.

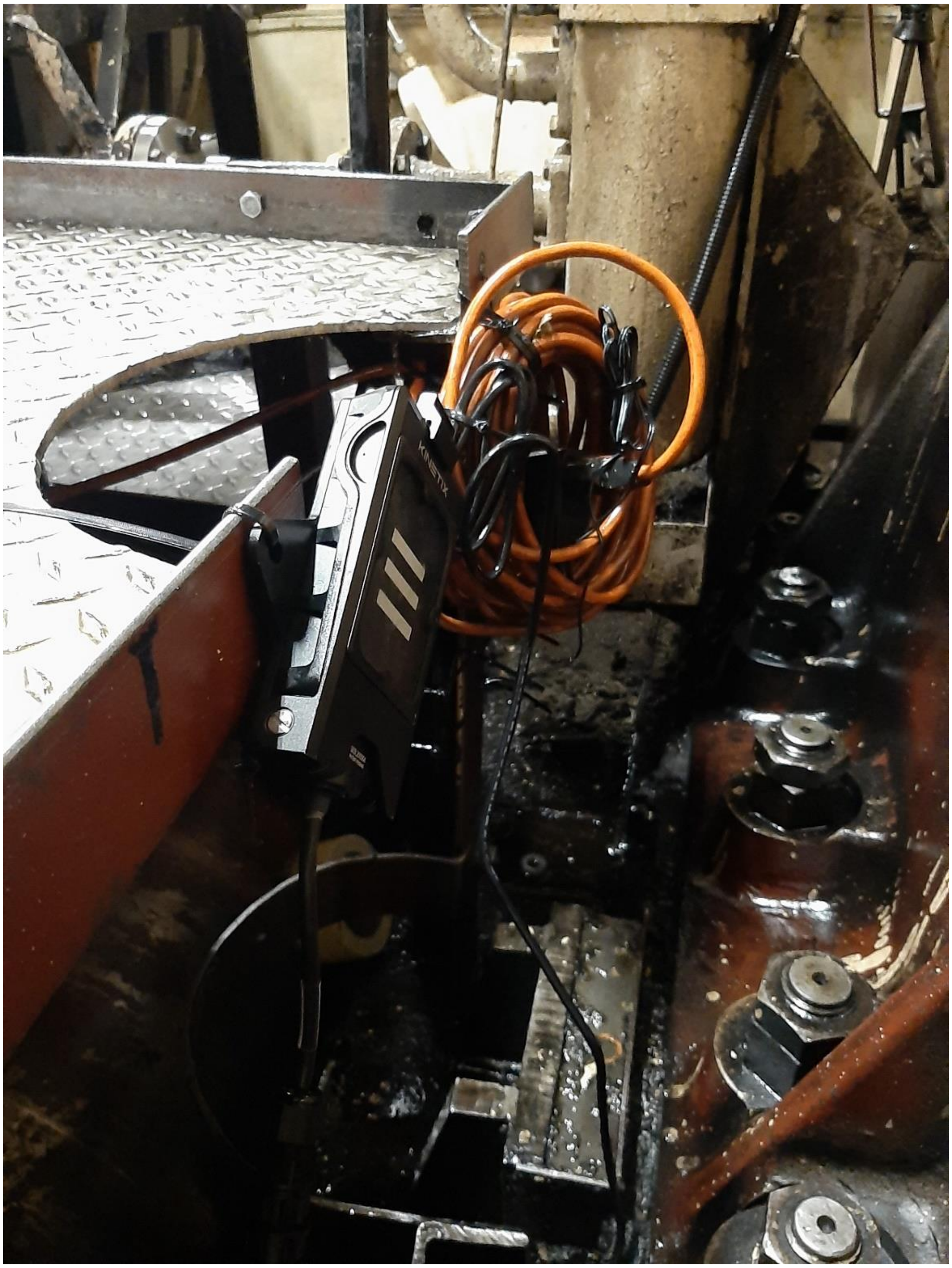

Figure 4-23 - New sensor locations for future data collection rounds

The sensor uptime schedule for Round 2 data collection is given in Figure 4-24.

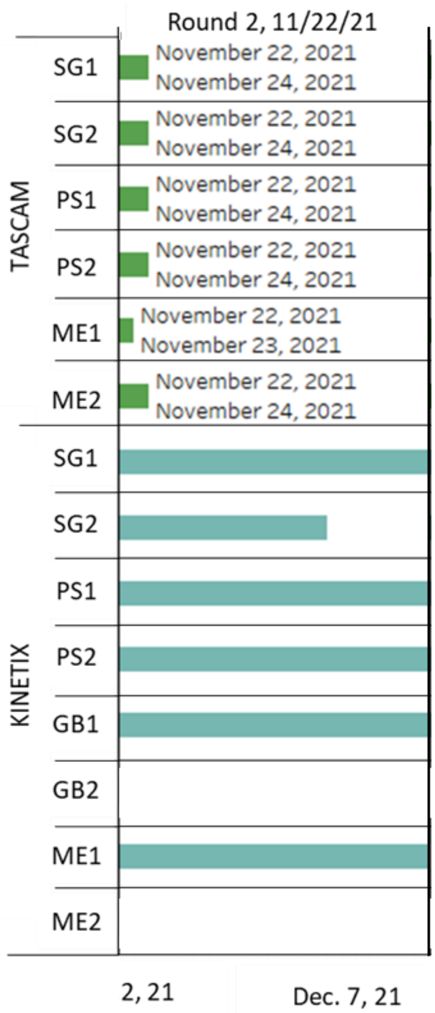

Figure 4-24 - Sensor up-time schedule, Round 2 data collection

4.2.6. Hydrophone Test Deployment

To ensure that the hydrophone measurements were fit for purpose and that it was possible to identify ferry noise and determine key tonal components, a test deployment was conducted in Brentwood Bay, at the Saanich inlet north of Victoria. The hydrophone was configured for deployment from the side of the Allsalt Maritime trials boat and took measurements of the MV Klitsa ferry during its normal operations. Measurements were taken to the southwest of Senanus island on the Brentwood Bay to Mill Bay ferry route, with the approximate measurement position given in Figure 4-25, and an example of the relative position of the Allsalt trials boat to MV Klitsa given in Figure 4-26.

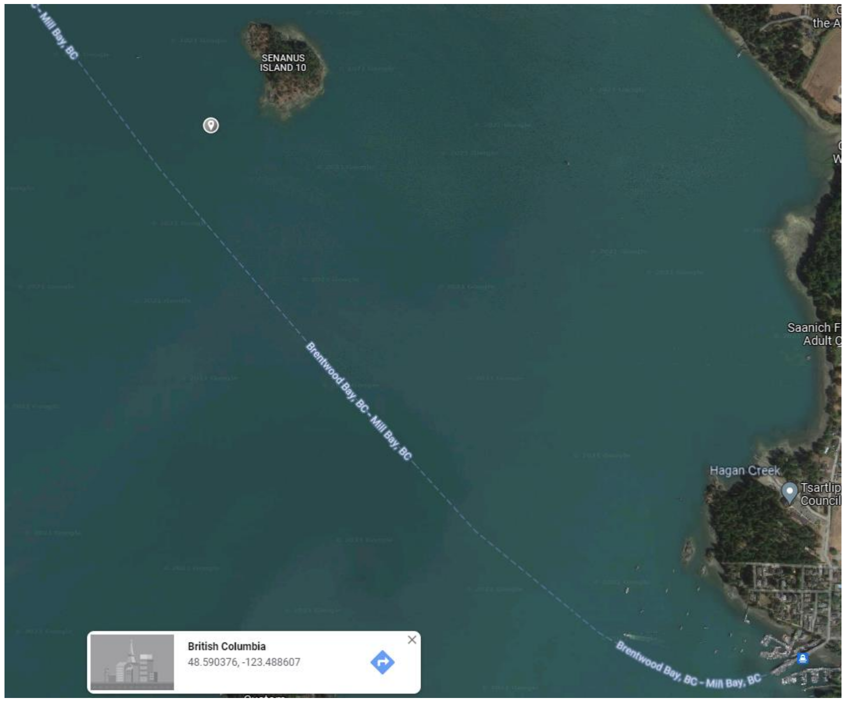

Figure 4-25 - Approximate hydrophone trial deployment location given by grey dot in top left corner.

Figure 4-26 - Relative position of Allsalt Maritime trials boat to MV Klista at closest measurement point

Results from this trial deployment showed the intended setup for the hydrophone was adequate for the intended Round 3 and Round 4 data collection activities, with ferry noise being audible and key tonal components identifiable in the frequency analysis of the test recordings.

4.2.7. Round 3 Data Collection

In addition to the standard noise and vibration measurements taken in the previous data collection rounds, this round included hydrophone measurements for the first time. This first phase of hydrophone deployment saw two hydrophones deployed close to the terminals at either end of the Nanaimo/Vancouver ferry route. The aim of data collection in these areas is to capture the URN profile of the Queen of Oak Bay as she accelerates out of or decelerates into dock at either end.

The hydrophones at these locations were deployed in an unattended configuration with a launch box to provide additional power and storage, as detailed in Section 4.2.1.3. In addition to this, to control the depth of the sensor in the water column the hydrophones were suspended from a small inflatable buoy via a support line and a small weight and secured to the handrail of the walkway to the side of the Queen of Oak Bay's dock. An example of the installation at the Departure Bay installation location is given in Figure 4-27, and the location of both installations relative to the surrounding area is given in Figure 4-28.

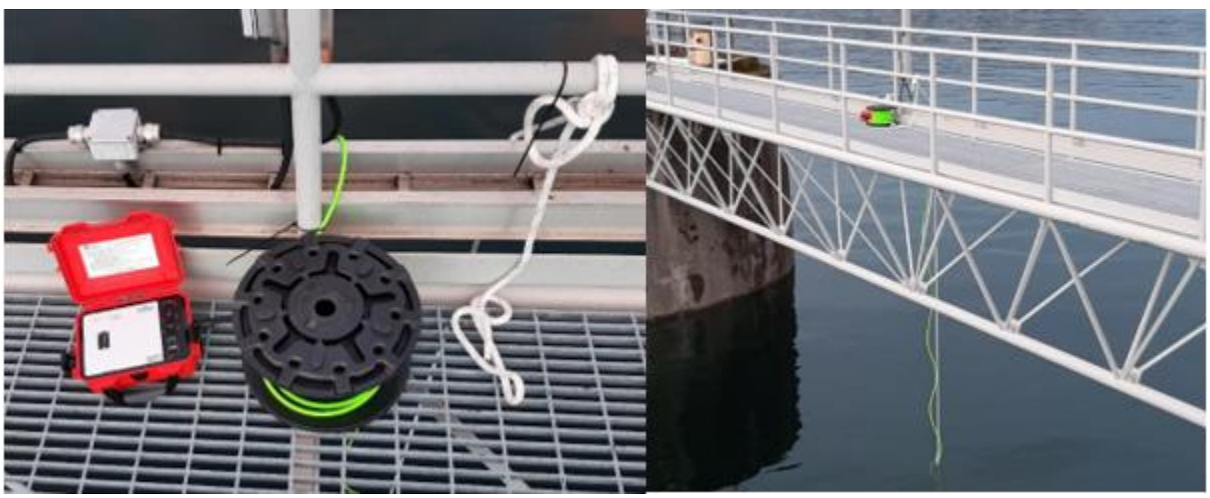

Figure 4-27 - Terminal location hydrophone deployment example for Departure Bay.

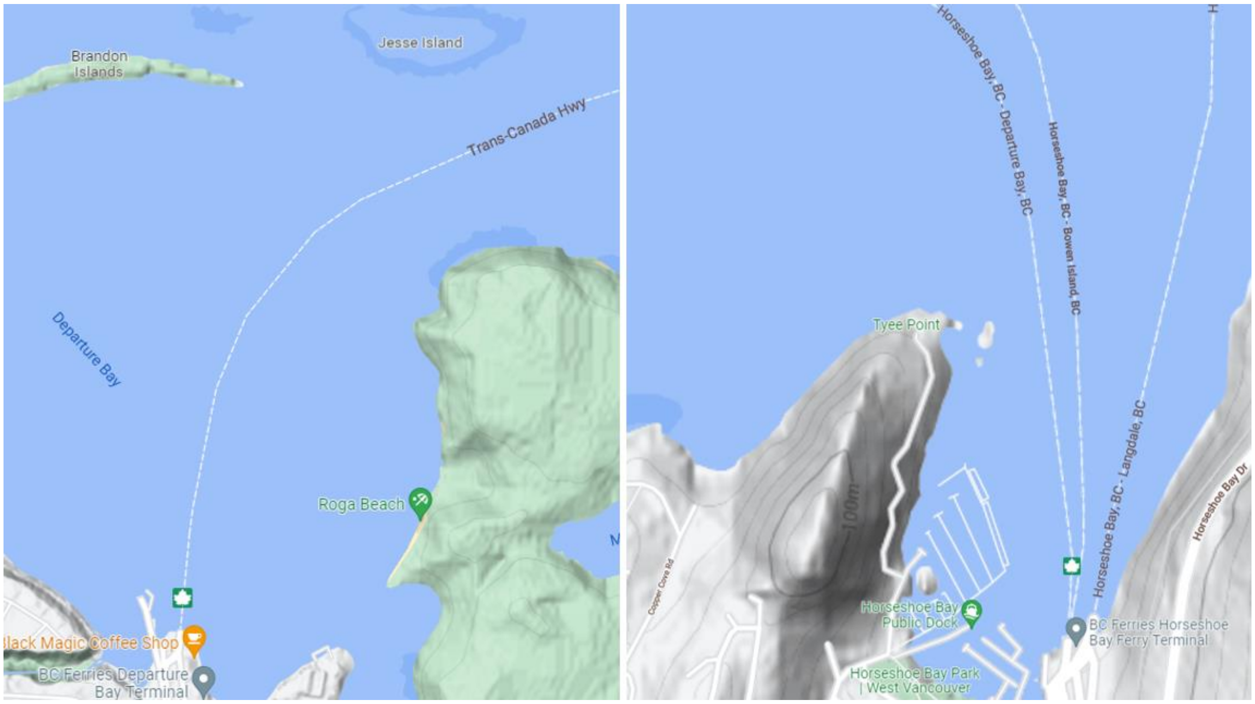

Figure 4-28 - Departure Bay (left) and Horseshoe Bay (right) ferry terminal areas

The hydrophones were deployed at Departure Bay on December 13th, 2021, and at Horseshoe Bay on December 14th, and were left installed for the maximum run time of the sensors on both dates, with this being around eight hours.

Unfortunately, the initial installation was not sufficient for the extreme tidal range of the installation areas, where the water can at times totally recede. This resulted in periods where the hydrophone was left suspended in air, wholly out of contact with the water. This resulted in a change in the deployment method for these measurement activities, which will be discussed in Section 4.2.8.

During the Round 3 data collection period, all Tascam noise sensors operated for their maximum theoretical measurement duration without issue.

The End 2 gearbox Kinetix sensor location did not begin recording until a few days into the deployment. This delay was observed to be the result of a setup flag in the system which required acceleration above a certain threshold to begin recording being incorrectly turned on. The data following on from this threshold event was observed to match expectations for level and frequency content for the main engine room machinery space.

The sensor uptime schedule for this phase of data collection is given in Figure 4-29.

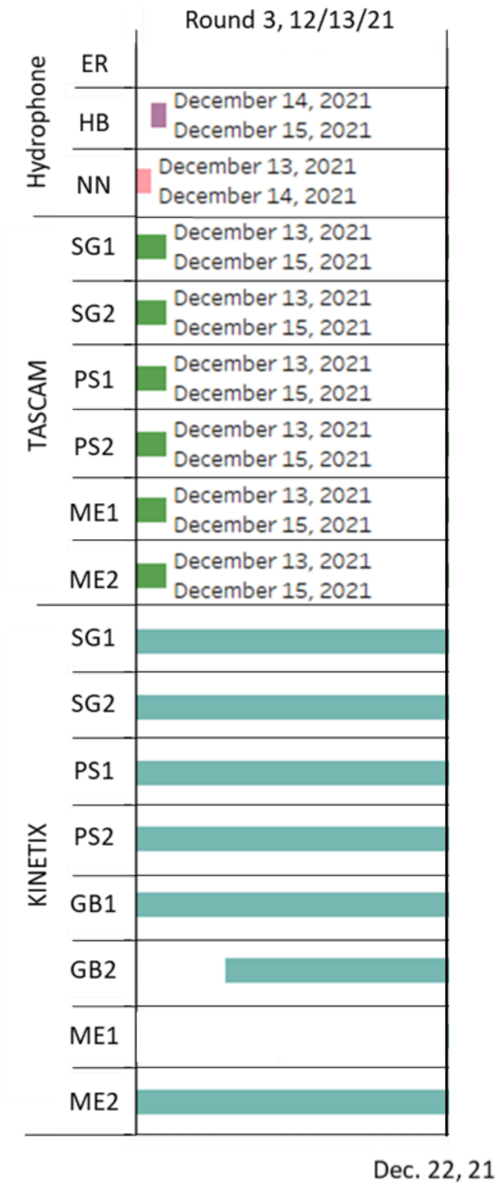

Figure 4-29 - Sensor up-time schedule, Round 3 data collection

4.2.8. Round 4 Data Collection

Round four is the final data collection phase of this project and comprises the highest number of deployed sensors: two hydrophones, six Tascam systems, and eight Kinetix systems.

The two hydrophone deployments comprise one "terminal" deployment as detailed in 4.2.7, and one on-boat deployment. The terminal deployment method used in the previous section was found to be inappropriate because of the large tidal range at the deployment sight and a simpler deployment method was used instead. The hydrophone was attached to a rope-and-sinker arrangement and attached at a height of 2 m from the sinker, with the other end of the arrangement being secured to the same attachment point as shown in Figure 4-27 at Departure Bay. This resulted in the hydrophone being submerged at all points during the measurement period, although there were concerns around the nature and the value of the data from this measurement point due to the shallow depth of the water column and the effect this has on propagation generally.

The second hydrophone deployment was done in an “over the side” style, as discussed in Section 4.2.6. This measurement location allowed several “pass-by” events as Queen of Oak Bay made her transits. The approximate location is given in Figure 4-30.

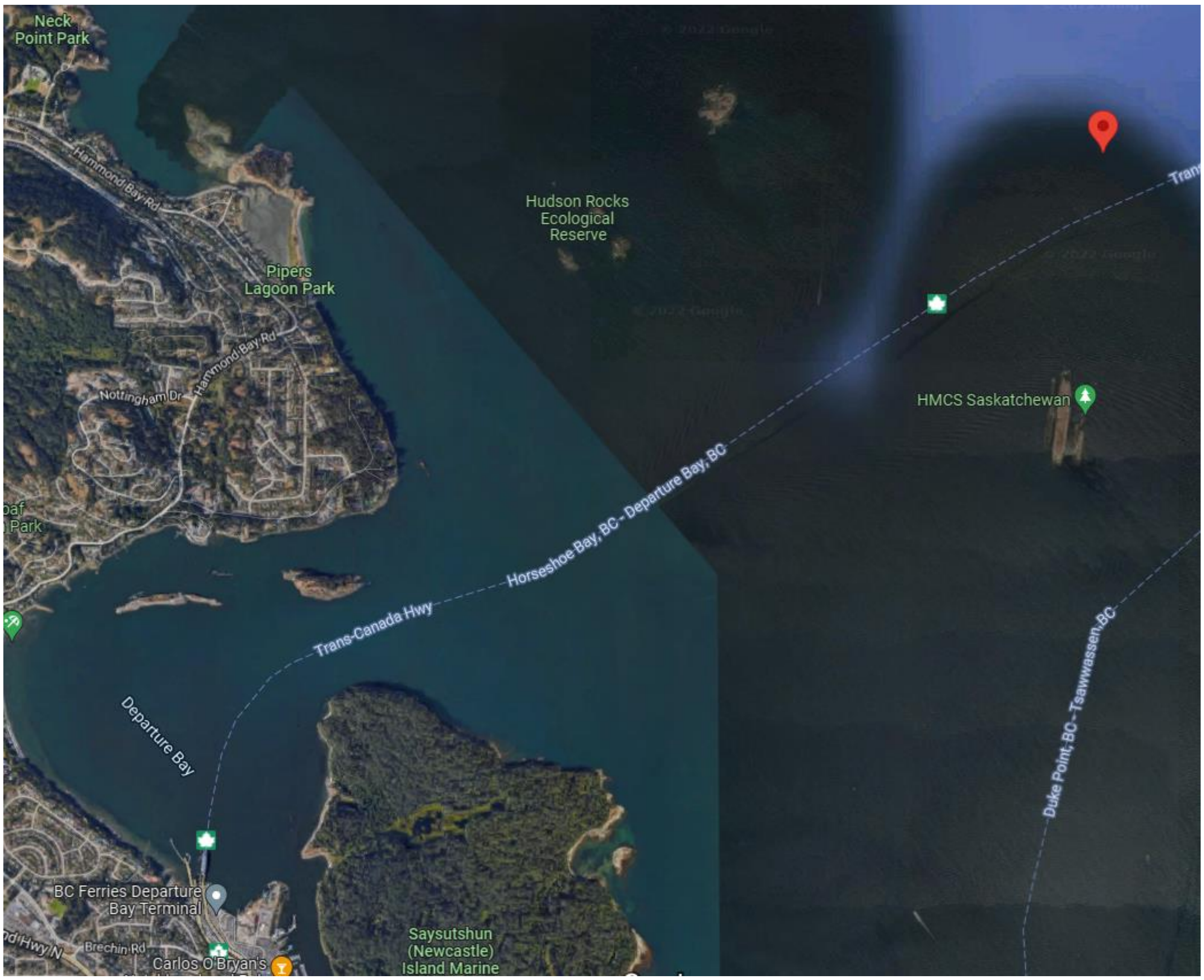

Figure 4-30 - Approximate location of en route measurements relative to the Ferry port at Nanaimo, position given by red pin in top right corner

The initial scope of work specified a total of ten measurements to be taken, but limitations in the en route measurement method made this difficult to achieve, resulting in a total of seven pass-by events being recorded. However, in post processing the data, we were able to ascertain that additional data would not significantly increase the statistical significance of the results and we are confident that sufficient data was gathered during these pass-by events.

The full log of which pass by events were captured, with accompanying photographs, is given in *APPENDIX A – En Route Measurement Data Recording Log*

The sensor uptime schedule for this round of data collection is given in Figure 4-31.

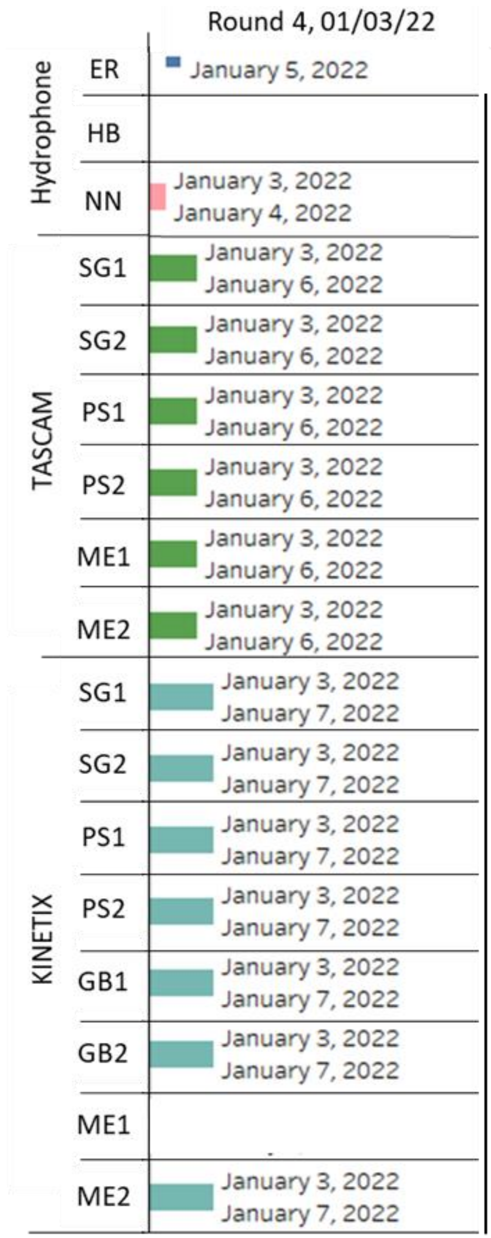

Figure 4-31 - Sensor uptime schedule, Round 4 data collection

5. Signal Processing Overview

Data collected from all three sensor types (Kinetix, Tascam, Hydrophone) was recorded in a raw time-history format, i.e., it is a record of how much the raw signal varied as a function of time. Whilst this data is useful for determining where noise and vibration levels may increase and where there are specific features of interest (such as onset of engine vibration, cavitation etc.), it is not easy to use to determine specific characteristics of the signal in an intelligent way. It is common for this kind of analysis to consider signals in the frequency domain instead. For the purposes of this analysis, it was deemed appropriate to use a narrowband analysis approach.

Narrowband analysis allows us to isolate a specific period in each time history and analyze the frequency content in that period. Frequency content is directly related to the operating speeds and noise profiles of specific pieces of equipment, such as the speed of rotation of the propeller shaft, main engine firing rate, pump motor operating speeds etc. Theoretically and to a first approximation, because each of the three measurement paradigms (vibration, noise, URN) are connected physically to some extent, this narrowband analysis should allow us to track the energy at a specific frequency as it is propagated from its source (vibration) into the surrounding media (air or water). This in turn allows us to build a model of which machinery sources have the largest impact on sound propagated out into the water and will have the biggest impact on the overall URN profile.

Data for each sensor type is first segmented into time-aligned X-second segments, and then transformed into the frequency domain via Welch's method. Because each of the three data types is sampled with a different sample rate, it is necessary to adjust the application of Welch's method. Welch's method contains provisions for processing a time history with a set of moving windows with fixed characteristics. By fine-tuning the length and number of windows to account for the difference in sample rate, it is possible to convert the time histories to the frequency domain with the same frequency resolution. A lower frequency resolution may mask areas in which two machinery tones are evident (e.g., if the resultant frequency domain data has a frequency resolution of 2 Hz, then a tone at 14 Hz and 15 Hz will be covered by the same data point, whereas a 0.5 Hz frequency band allows us to separate these tones. An example comparison between the time history and frequency domain data is given in Figure 5-1.

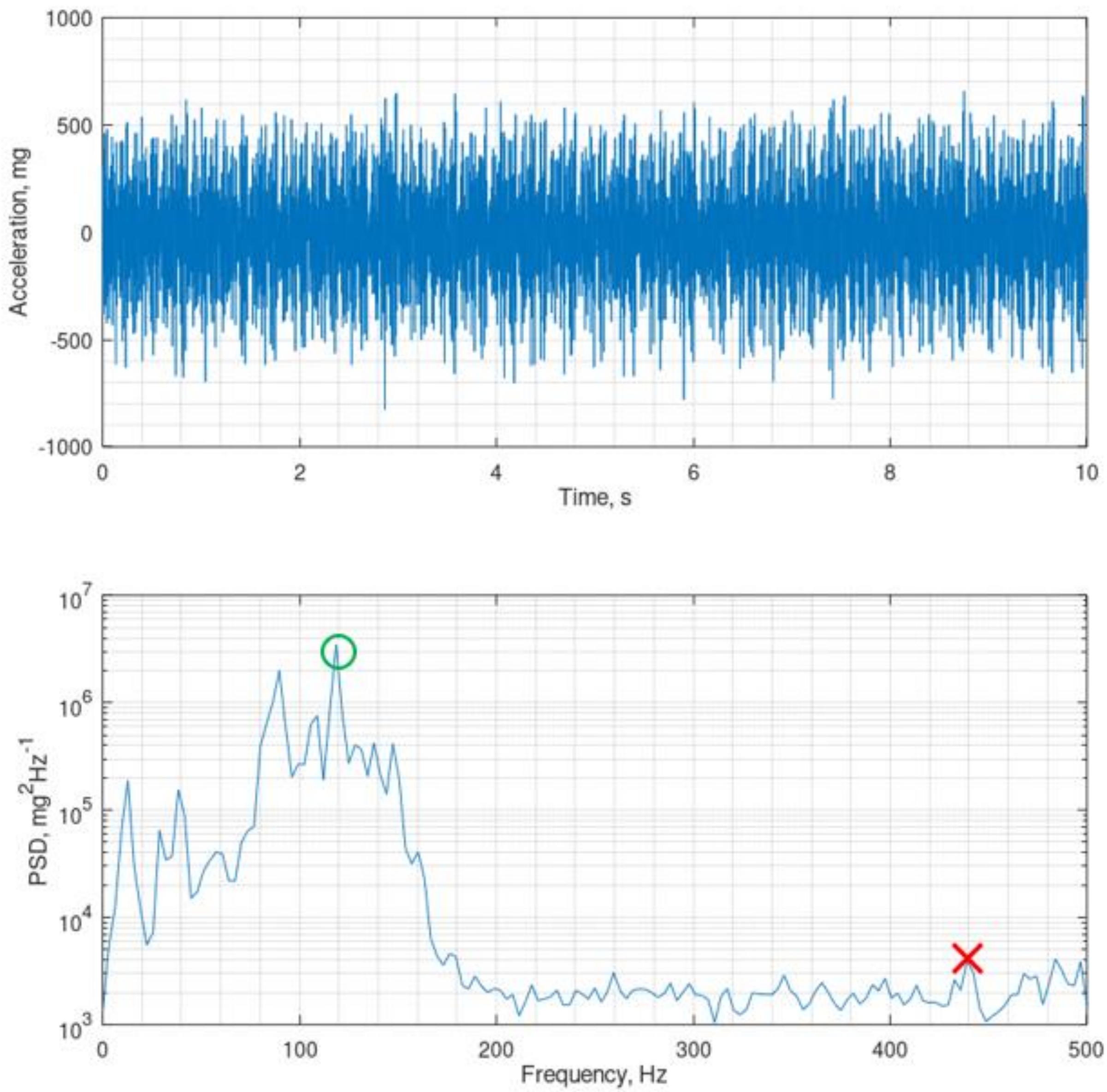

Figure 5-1 - Comparison of time history (top) and resultant power spectral density (bottom) for an arbitrary 10 s acceleration sample. Green circle indicates clear peak, red cross indicates peak typically discarded by peak-finding algorithm

In this example, we can see that the dominant energy in this vibration data sample occurs below 200 Hz, with clear and evident peaks within this range pertaining mostly to the machinery operating in this space.

Following the conversion to the frequency domain a peak-finding algorithm is employed to extract “tonal” components. In this context, tonal components are features in the PSD which are narrow in frequency width (e.g., whilst there is a lot of energy in the broad hump in Figure 5-1 between 80 and 140 Hz, this is “broadband” noise), and have energy significantly greater than the surrounding region (e.g. the peak marked with a green circle in Figure 5-1 is prominent above the surrounding frequency range, whilst the peak marked with a red x is still technically a peak, but is not sufficiently prominent to consider in our analysis). Airborne noise and URN were processed in the same way.

In addition to the peak magnitude and frequency of each frequency domain data set, characteristics of each peak were extracted to aid in describing and ranking the likely value of each extracted peak. These characteristics were the width of the peak and the prominence of the peak. Width is the distance between zero-crossings of the peak, whilst prominence is the ratio of the peak being considered to the average of the power spectral density in a windowed region either side of the peak. The width is a useful indicator of the amount of energy contained by the peak, and the prominence is a useful indicator as to whether the peak is significant enough to be included in the analysis.

6. Application of Machine Learning

The following sections outline the methods employed to construct a relationship between dry side noise and vibration measurements with underwater radiated noise using machine learning methods.

6.1. Feature Extraction Process

A total of 70 minutes of URN data was obtained from the en route measurements, and the corresponding noise and vibration data was extracted from the database to produce three time-matched datasets, which are taken from Round 4 of data collection (see Figure 4-31). This subset of data, along with the corresponding en route URN data, formed the basis of analysis in this project. For simplicity, each ten-second segment of data will be referred to as a 'signal'. Therefore, there are 420 signals (70 minutes at a rate of six signals per minute) for every sensor.

From the index of peak frequency events produced via the method outlined in the prior section, four attributes were selected as descriptors: frequency (the x-axis value of the peak), amplitude (the y-axis value of the peak), width (the distance between a given percentage of the max amplitude of a peak either side of its frequency), and prominence (the relative height of the peak compared to the root-mean-square value of the signal within a defined window). An example of three synchronous signals from different sources in the time domain and frequency domain is shown in Figure 6-1.

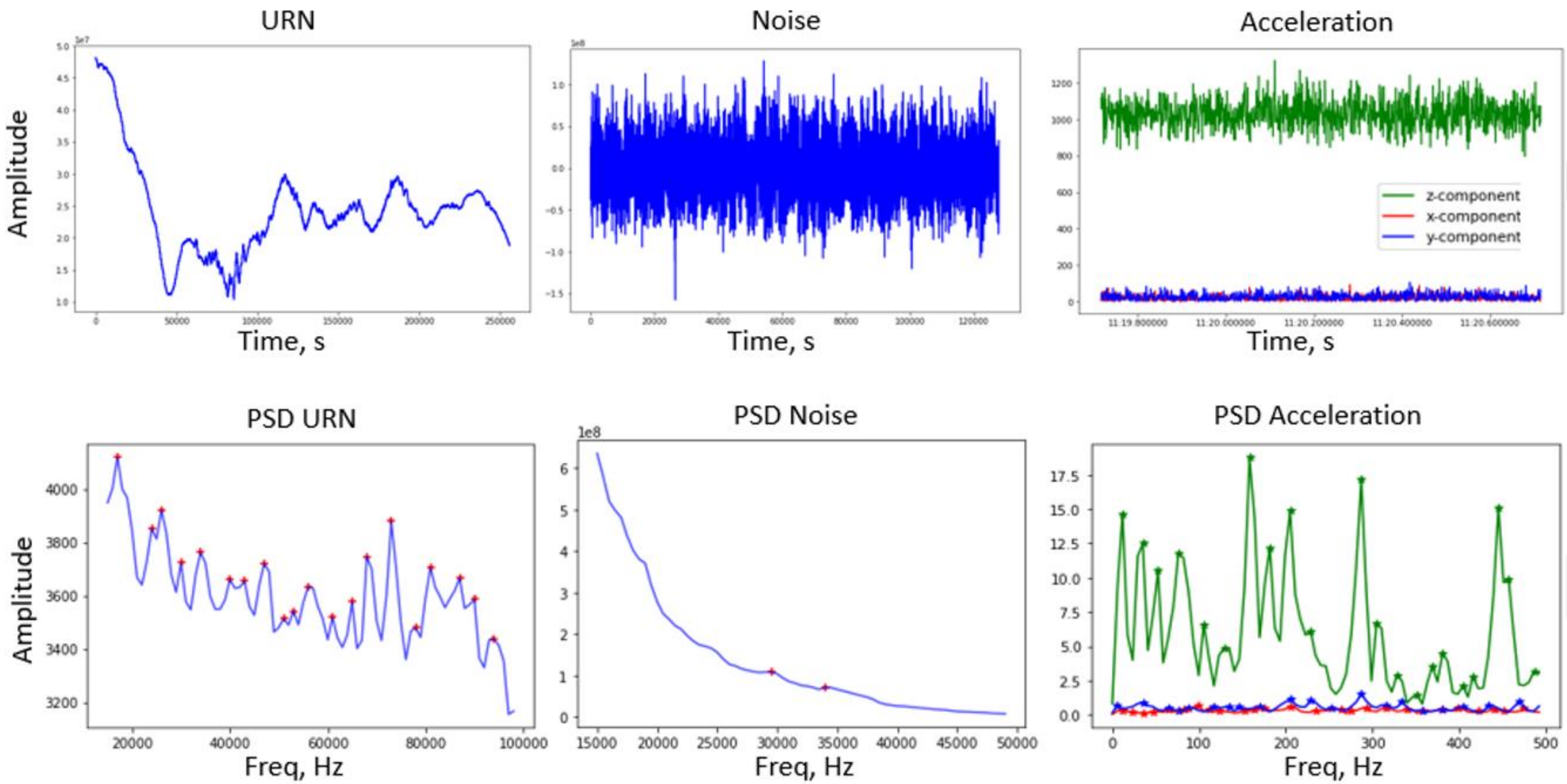

Figure 6-1- Synchronous signals from the hydrophone, Tascam, and Kinetix (left to right) in the time domain (top) and peak features in resultant PSD (bottom)

The two things that needed to be decided were which peaks and which attributes of peaks should be considered. For this purpose, the peaks were sorted according to their amplitude and then the first *n* peaks, and their *x* attributes were compared for different *n* and *x* values. The audio (URN and noise) signals were compared for four different combinations of *n* and *x* as follows:

a. Two attributes (frequency, amplitude) of 25 peaks
b. Four attributes (frequency, amplitude, width, and prominence) of 25 peaks
c. Two attributes (frequency, amplitude) of 50 peaks
d. Four attributes (frequency, amplitude, width, and prominence) of 50 peaks

Figure 6-2 shows the feature matrix for audio signals in Case D where all 4 attributes were taken of the first 50 peaks of each transform. The letters f, a, w, and p respectively stand for frequency, amplitude, width, prominence. The superscript on these letters indicates the index of the peak. As Figure 6-2 illustrates, there are 200 columns (comprising 50 peaks with four attributes each) in the feature matrix in Case D.

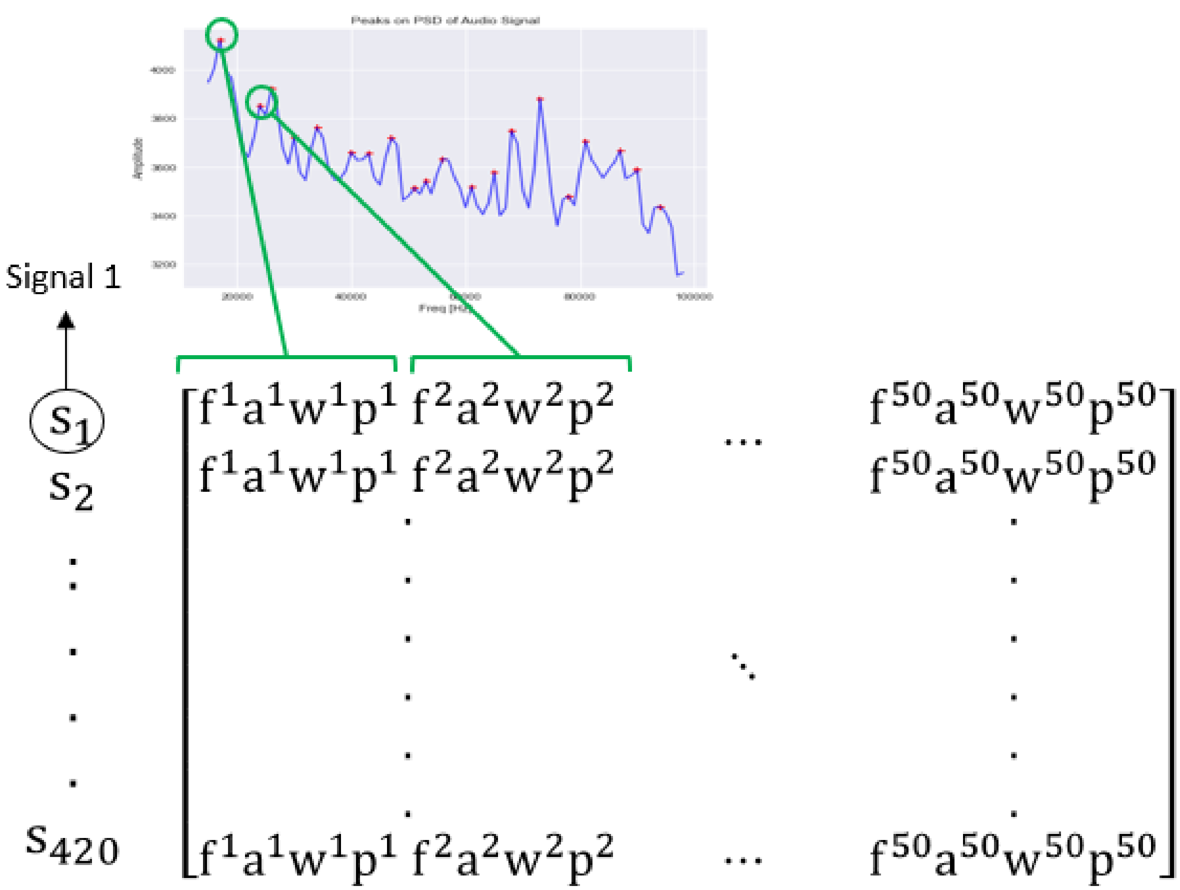

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Figure 6-2 – The feature matrix for the audio signal in the case of using 4 attributes of the first 50 peaks

Vibration signals were processed in the same way, except that vibration signals are triaxial (i.e., they comprise horizontal, lateral, and vertical components), and this triples the number of features. Also, since the sampling rate of Kinetix measurements is much lower than audio signals (1 kHz for the Kinetix vibration measurements, 256 kHz for the URN measurements and 48 kHz for the Tascam measurements), fewer peaks were detected for vibration signals. Therefore, the condition n = 50 was excluded, and only two combinations of peaks and attributes were tried:

a. 2 attributes (frequency, amplitude) of 25 peaks for each direction (X, Y, Z).
b. 4 attributes (frequency, amplitude, width, and prominence) of 25 peaks for each direction (X, Y, Z).

Figure 6-3 illustrates the feature matrix for the vibration signal in Case B, where all four attributes are taken of the first 25 peaks for each axis. There are 300 columns (four attributes in three axes for 25 peaks) in the feature matrix in Case B.

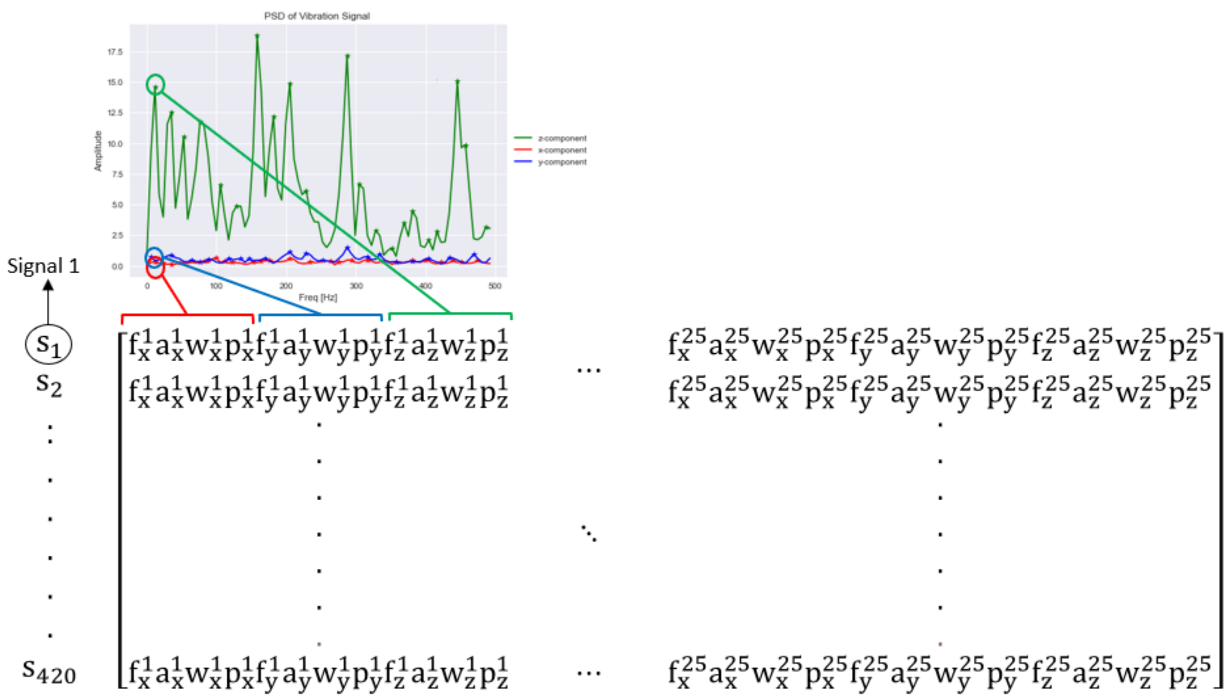


Figure 6-3 – The feature matrix for vibration signal in the case of using 4 attributes of the first 25 peaks for each direction

6.2. Feature Selection Using Noise and Vibration Data

This section explains the machine learning algorithm that was implemented on noise and vibration signals to select the best combinations of features. Using the machine learning algorithm, a relationship between noise and vibration data was derived and used for prediction.

The machine learning techniques were initially developed and refined using the dry side noise and vibration data as these datasets were expected to have features that were closely related as pairs of noise and vibration measurements were taken in approximately the same place. The set of features that were identified as giving the best results when using machine learning to relate the noise and vibration data could then be used in the next section to study of the relationship between URN and vibration.

Using the four combinations of features for audio signals and two combinations of features for vibration signals outlined in Section 6.1, a total of eight cases were examined to study the relationship between noise and vibration:

1. Two attributes of 25 peaks from audio signal vs. Two attributes of 25 peaks from vibration signal;
2. Four attributes of 25 peaks from audio signal vs. Two attributes of 25 peaks from vibration signal;
3. Two attributes of 50 peaks from audio signal vs. Two attributes of 25 peaks from vibration signal;
4. Four attributes of 50 peaks from audio signal vs. Two attributes of 25 peaks from vibration signal;
5. Two attributes of 25 peaks from audio signal vs. Four attributes of 25 peaks from vibration signal;
6. Four attributes of 25 peaks from audio signal vs. Four attributes of 25 peaks from vibration signal;
7. Two attributes of 50 peaks from audio signal vs. Four attributes of 25 peaks from vibration signal;
8. Four attributes of 50 peaks from audio signal vs. Four attributes of 25 peaks from vibration signal.

Noise signals are expected to be highly correlated to vibration signals since Tascam units were installed very close to the Kinetix system in six locations of Queen of Oak Bay. This was the reason for using the noise and vibration relationship to detect the best set of features. Before detailing the analytical methods used in this assessment, it is worth mentioning that one of the Tascam units (SG1) developed a clock problem in Round 2 of data collection, such that it was offset from all other measurement systems. Even though necessary steps had been taken to solve the problem in Round 3, data from this unit could not be synchronized with other sources, therefore, this location was excluded from the analysis. [2]

The Tascam units and Kinetix systems recorded data constantly during the whole period of data collection, resulting in hundreds of gigabytes of data. To streamline and focus analysis, only the subset of the data which is aligned with URN data collection periods has been analyzed. Therefore, data were sampled in several points at the data collection timeline, and the section which was synchronous to en route URN data is described here. These synchronous results were used for the rest of the analysis

The flowchart in Figure 6-4 represents the steps taken to examine each of the eight combinations of features.

[2] *Whilst Case 8 is used here to explain the methodology, the other seven cases are studied in the same way and the result for all cases is given at the end of this section.*

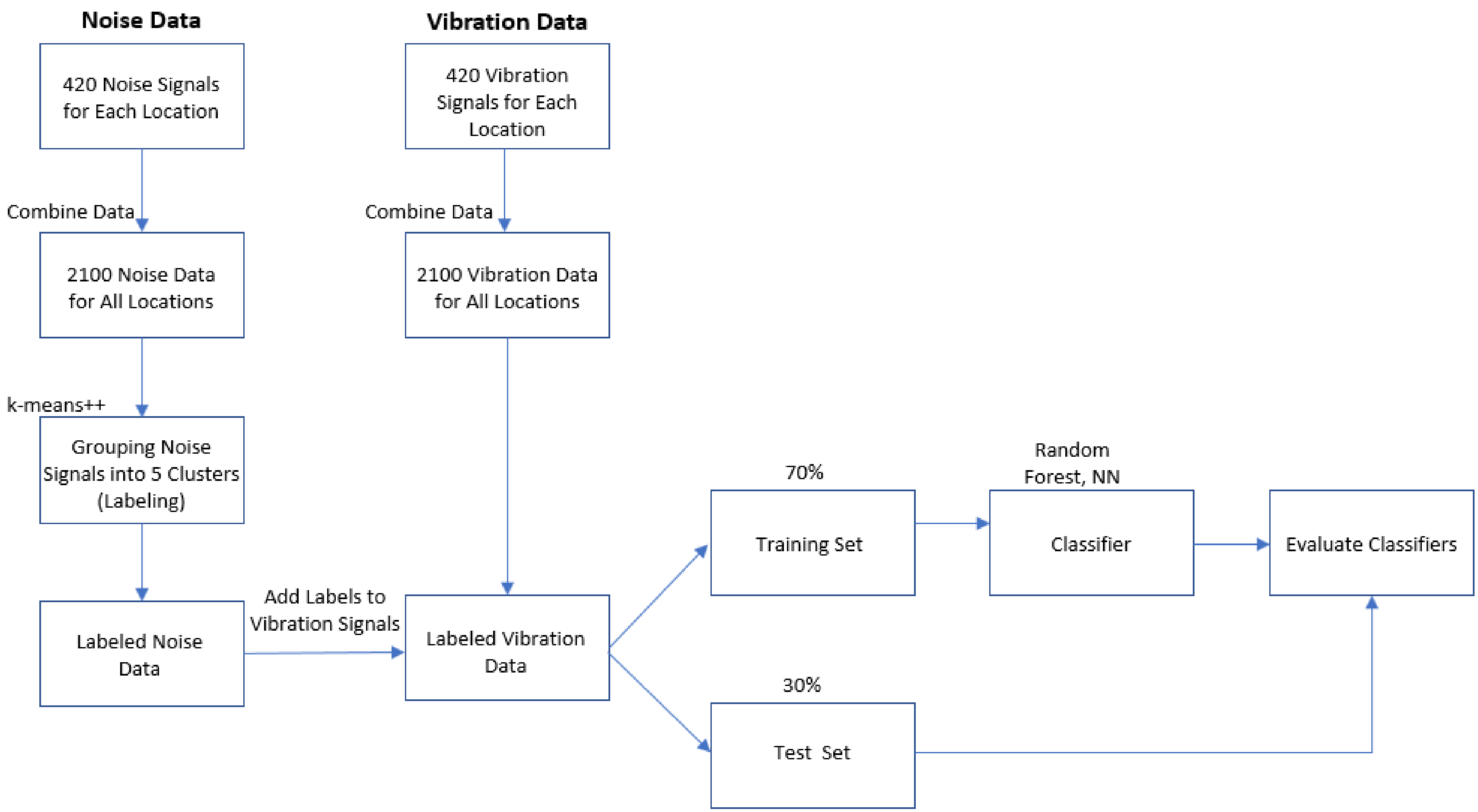


Figure 6-4 – Step-by-step diagram for application of machine learning to noise and vibration data

At the first step of studying the relationship between noise and vibration data, as the flow diagram shows, noise signals from different sensors (locations: ME1, ME2, PS1, PS2, SG2) were extracted and combined. Figure 6-5 shows the matrix of combined noise signals. This matrix has 2100 rows (420 signals at five locations) and 200 columns (50 peaks with four attributes).

$$\begin{array}{l} \text{ME1} \\[40pt] \text{ME2} \\[40pt] \text{PS1} \\[40pt] \text{PS2} \\[40pt] \text{SG2} \end{array} \left[\begin{array}{c} \begin{bmatrix} f^1a^1w^1p^1 & \cdots & f^{50}a^{50}w^{50}p^{50} \\ \vdots & \ddots & \vdots \\ . & \cdots & . \end{bmatrix}_{420\text{x}200} \\ \begin{bmatrix} f^1a^1w^1p^1 & \cdots & f^{50}a^{50}w^{50}p^{50} \\ \vdots & \ddots & \vdots \\ . & \cdots & . \end{bmatrix}_{420\text{x}200} \\ \begin{bmatrix} f^1a^1w^1p^1 & \cdots & f^{50}a^{50}w^{50}p^{50} \\ \vdots & \ddots & \vdots \\ . & \cdots & . \end{bmatrix}_{420\text{x}200} \\ \begin{bmatrix} f^1a^1w^1p^1 & \cdots & f^{50}a^{50}w^{50}p^{50} \\ \vdots & \ddots & \vdots \\ . & \cdots & . \end{bmatrix}_{420\text{x}200} \\ \begin{bmatrix} f^1a^1w^1p^1 & \cdots & f^{50}a^{50}w^{50}p^{50} \\ \vdots & \ddots & \vdots \\ . & \cdots & . \end{bmatrix}_{420\text{x}200} \end{array} \right]_{2100 \text{ x } 200}$$

Figure 6-5 – Noise signal combined matrix in the case of using four attributes of the first 50 peaks

Since the noise signals are not classified and do not have a label, an unsupervised learning method was needed to approach this data. The term "label" in classification indicates the category or class of a record in the dataset. For example, if a dataset is supposed to be grouped into two categories of records; those that caused cavitation and those that did not cause cavitation, a label 'cavitation' or 'non-cavitation' needs to be assigned to each record in the dataset to provide context so that a machine learning model can learn from it.

Clustering is an unsupervised learning technique that helps to group instances based on their similarity. The simple and classic clustering technique is *k-means++* that forms clusters of data based on the similarity of Euclidean distance between instances and centroids of the clusters. Using *k-means++* clustering, the records in the noise dataset were grouped into k classes such that all records in the same cluster are similar to each other, whilst records in different clusters are dissimilar. The number of clusters (k) is a hyperparameter which is set to five. This parameter value was chosen after using a heuristic technique on URN data and inspecting the calculated clusters in detail. The method used to select the value of k is given in Section 7. Figure 6-6 shows an example of a feature matrix of noise signals after labeling.

$$
\begin{array}{c}
 \\ s_1 \\ s_2 \\ \vdots \\ s_{2100}
\end{array}
\begin{array}{c}
\begin{array}{ccccccccccc}
f^1 & a^1 & w^1 & p^1 & & f^{50} & a^{50} & w^{50} & p^{50} & \text{Labels}
\end{array} \\
\begin{bmatrix}
256.13 & 0.008 & 51.2 & 1.05 & \cdots & 5532 & 0.0005 & 819.36 & 0.95 & 1 \\
307.36 & 0.007 & 67.3 & 1.11 & & 5635 & 0.0004 & 726.92 & 0.98 & 5 \\
 & \vdots & & & \ddots & & \vdots & & & \vdots \\
4661.14 & 0.001 & 131.3 & 0.99 & \cdots & 6557 & 0.0004 & 2749.23 & 0.94 & 2
\end{bmatrix}
\end{array}
$$

Figure 6-6 – An example of feature matrix of noise signals after labeling, where the parameters are given along the top of the matrix, and the signal index is given along the side

Following on from clustering, each signal was assigned a label that can be interpreted as noise level. [3]

Clustering, however, is not the final objective. Clustering is simply a means to clean up and simplify data for the supervised learning task. The final step in preparing data for supervised learning was to combine vibration signals from the same locations for which the noise signals were available (ME1, ME2, PS1, PS2, SG2). A matrix with 2100 rows (420 signals at five locations) and 300 columns four attributes in three axes at 25 peaks) was obtained for this purpose, as demonstrated in Figure 6-7.

[3] *In this context, "noise level" refers to the root mean square (RMS) of the magnitude of a group of peaks, not the more usual acoustic context.*

$$
\begin{array}{l}
\text{ME1} \\ \\ \\ \text{ME2} \\ \\ \\ \text{PS1} \\ \\ \\ \text{PS2} \\ \\ \\ \text{SG2}
\end{array}
\left[
\begin{array}{l}
\left[\begin{matrix} f_x^1 a_x^1 w_x^1 p_x^1 f_y^1 a_y^1 w_y^1 p_y^1 f_z^1 a_z^1 w_z^1 p_z^1 & \cdots & f_x^{25} a_x^{25} w_x^{25} p_x^{25} f_y^{25} a_y^{25} w_y^{25} p_y^{25} f_z^{25} a_z^{25} w_z^{25} p_z^{25} \\ \vdots & \ddots & \vdots \\ . & \cdots & . \end{matrix}\right]_{420\text{x}300} \\
\left[\begin{matrix} f_x^1 a_x^1 w_x^1 p_x^1 f_y^1 a_y^1 w_y^1 p_y^1 f_z^1 a_z^1 w_z^1 p_z^1 & \cdots & f_x^{25} a_x^{25} w_x^{25} p_x^{25} f_y^{25} a_y^{25} w_y^{25} p_y^{25} f_z^{25} a_z^{25} w_z^{25} p_z^{25} \\ \vdots & \ddots & \vdots \\ . & \cdots & . \end{matrix}\right]_{420\text{x}300} \\
\left[\begin{matrix} f_x^1 a_x^1 w_x^1 p_x^1 f_y^1 a_y^1 w_y^1 p_y^1 f_z^1 a_z^1 w_z^1 p_z^1 & \cdots & f_x^{25} a_x^{25} w_x^{25} p_x^{25} f_y^{25} a_y^{25} w_y^{25} p_y^{25} f_z^{25} a_z^{25} w_z^{25} p_z^{25} \\ \vdots & \ddots & \vdots \\ . & \cdots & . \end{matrix}\right]_{420\text{x}300} \\
\left[\begin{matrix} f_x^1 a_x^1 w_x^1 p_x^1 f_y^1 a_y^1 w_y^1 p_y^1 f_z^1 a_z^1 w_z^1 p_z^1 & \cdots & f_x^{25} a_x^{25} w_x^{25} p_x^{25} f_y^{25} a_y^{25} w_y^{25} p_y^{25} f_z^{25} a_z^{25} w_z^{25} p_z^{25} \\ \vdots & \ddots & \vdots \\ . & \cdots & . \end{matrix}\right]_{420\text{x}300} \\
\left[\begin{matrix} f_x^1 a_x^1 w_x^1 p_x^1 f_y^1 a_y^1 w_y^1 p_y^1 f_z^1 a_z^1 w_z^1 p_z^1 & \cdots & f_x^{25} a_x^{25} w_x^{25} p_x^{25} f_y^{25} a_y^{25} w_y^{25} p_y^{25} f_z^{25} a_z^{25} w_z^{25} p_z^{25} \\ \vdots & \ddots & \vdots \\ . & \cdots & . \end{matrix}\right]_{420\text{x}300}
\end{array}
\right]_{2100\text{ x }300}
$$

Figure 6-7– Vibration signal combined matrix in the case of using 4 attributes of the first 25 peaks

The labels obtained in the previous step then were added to the vibration feature matrix. Where there was a correlation between noise and vibration, the vibration signals that have the same label must share common properties and be distinguishable based on their labels. An example of the feature matrix of labeled vibration signals is shown in Figure 6-8.

	f_x^1	a_x^1	w_x^1	p_x^1	f_y^1	a_y^1	w_y^1	p_y^1	f_z^1	a_z^1	w_z^1	p_z^1		f_x^{25}	a_x^{25}	w_x^{25}	p_x^{25}	f_y^{25}	a_y^{25}	w_y^{25}	p_y^{25}	f_z^{25}	a_z^{25}	w_z^{25}	p_z^{25}	Labels
s_1	120	83000	12	1.6	141	50000	16	1.2	141	48000	32	1.7	…	248	14000	27	2.4	192	22000	50	1.2	54	1700	47	1.3	1
s_2	150	98000	26	1.5	298	17000	23	1.8	418	59000	16	1.6		386	28000	42	1.7	490	37000	26	1.7	215	1800	22	1.2	5
⋮						⋮							⋱						⋮							⋮
s_{2100}	400	78000	19	0.66	413	99000	52	0.98	285	66000	44	1.9	…	115	25000	33	2.3	390	27000	18	1.5	166	1900	27	1.5	2

Figure 6-8 - An example of feature matrix of vibration signals after adding the corresponding labels

With a label in front of each row in the feature matrix, the final output to be predicted can be defined and vibration signals can be classified. For this purpose, the dataset was split into training and testing datasets with a 70:30 ratio. It means the classifier algorithm was trained on 1470 records and then tested on the whole dataset including the 630 unseen records.

Two classifying methods were implemented on the dataset: *Random Forest* and *Neural Network*. Random forest is a supervised learning algorithm which uses an ensemble learning method for classification and regression. The trees in random forests run in parallel without interactions between each tree during the building phase. It operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean predictions of the individual trees.

The Neural Network method is widely used for classification in academia and industrial applications due to its efficiency and its capability of finding the more important features automatically and properly weighting features.

For the Neural Network method, the ratio of training, validation, and testing dataset was 70:15:15. The validation dataset was used to tune the model's hyperparameters, however, like the testing dataset, it was held back from training the model.

In most cases, the Neural Network algorithm outperformed the Random Forest on the test dataset. However, Random Forest performed very well on the training set and its total accuracy is higher than the Neural Network method. The total accuracy of prediction for different cases, for the two algorithms, are given in Table 6.1. An example of the resulting confusion matrix (Neural Network algorithm for Case 8) is demonstrated in Figure 6-9.

Table 6.1 – Results from implementing two machine learning methods to classify vibration signals based on labeled noise signals. The highlighted row indicates the set of features that led to the best results

Case no.	Signal		Accuracy	
	Noise	Vibration	Random Forest	Neural Network
1	2 attributes _25 peaks	2 attributes _25 peaks	91.6	89.0
2	4 attributes _25 peaks	2 attributes _25 peaks	91.7	82.5
3	2 attributes _50 peaks	2 attributes _25 peaks	92.8	86.8
4	4 attributes _50 peaks	2 attributes _25 peaks	94.1	84.2
5	2 attributes_25 peaks	4 attributes _25 peaks	92.2	83.2
6	4 attributes _25 peaks	4 attributes _25 peaks	92.1	87.6
7	2 attributes _50 peaks	4 attributes _25 peaks	92.9	83.1
8	4 attributes _50 peaks	4 attributes _25 peaks	94.0	90.1

Figure 6-9 – The Confusion matrices resulted from the implementation of Neural Network algorithm on data using four attributes of the first 50 peaks of noise signals and four attributes of the first 25 peaks of vibration signals

As it can be seen from Table 6.1, we were able to classify vibration signals with high accuracy. The set of features that led to the highest accuracy is Case 8: *Four attributes of 50 peaks from audio signal versus four attributes of 25 peaks from the vibration signal*.

This set of features was selected as characteristics of the signals and was used in studying the relationship between URN and vibration data. It is understandable that some of these characteristics could be more informative than others. For example, in a vibration signal, it could be that peaks of transformation in one direction are more important than the others, or that the frequency and amplitude values of the peaks are more informative than the width and prominence.

The method that we used to select features is a heuristic method that allows us to specify the number of peaks and the attributes based on the results, instead of speculating about them.

At the last stage of studying noise and vibration signals, the level of noise was compared to the level of vibration. The aim of this step was to discover whether the more intense noise clusters correspond to the more intense vibration clusters. For this purpose, the centroid of each cluster was considered as the representative of that cluster and its intensity was calculated. The centroid for each cluster is the point from which the sum of the Euclidean distances of all samples that belong to that cluster is minimized. One way to express the intensity (or magnitude) is to measure the RMS of the amplitudes of peaks. Comparing the intensity level of the noise and vibration clusters, it was observed that the higher the intensity level of the noise cluster, the higher the intensity level of the vibration cluster.

From noise and vibration data analysis the best set of features was selected, and it was concluded that the methodology adopted was an effective approach for relating the audio and vibration data. This analysis was in fact a test for the accuracy of the method that later was implemented on URN and vibration data.

7. URN Prediction Accuracy

As it was mentioned earlier, 420 URN signals were obtained from en route measurement. Using the result of feature selection, four attributes of the first 50 peaks in PSD with the highest amplitude were extracted for these signals. The flowchart in Figure 7-1 represents the steps taken to examine relationship between URN and Vibration signals.

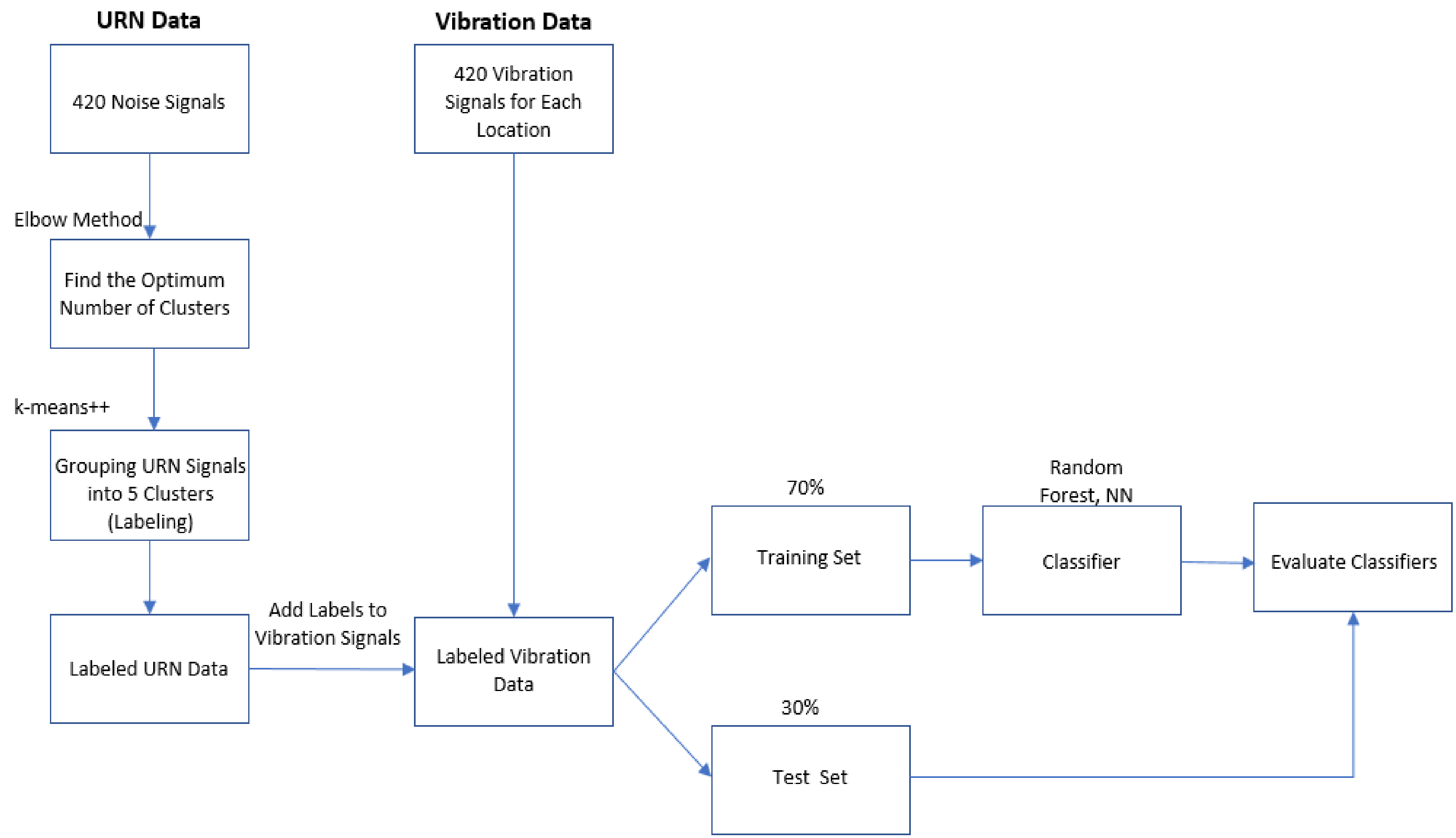


Figure 7-1 - step-by-step diagram for application of machine learning to vibration and URN signals

Like noise and vibration, the URN signals were clustered into several groups. There are various heuristic techniques for determining the correct number of groups, with the most common being the *elbow method.*

In the elbow method, the sum of squares of distance from centroid is calculated for all the samples in a cluster and called SSE (sum of squared error) of that cluster. The SSE values for all the clusters are added together to compute the total distortion. The total distortion will then be calculated for each number of clusters and graphed. The user looks for a change of slope from steep to shallow (an elbow) to determine the optimal number of clusters. Figure 7-2 shows the elbow method graph for the URN dataset.

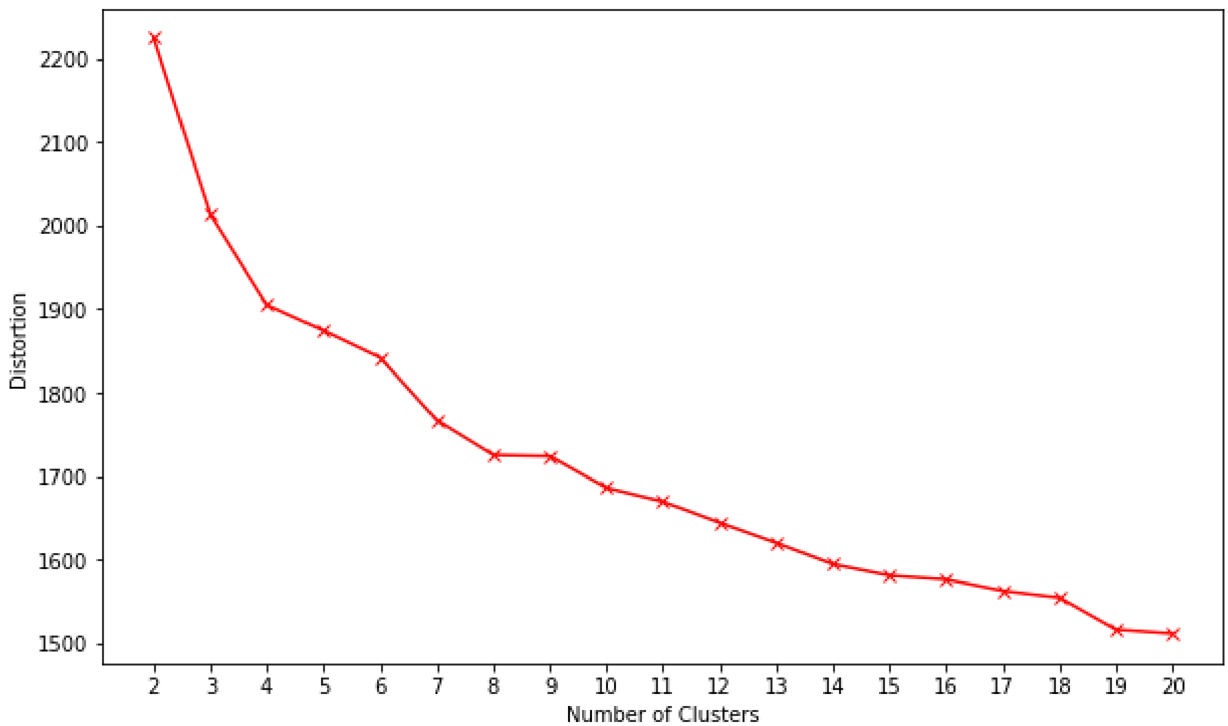


Figure 7-2 –Elbow method graph for the URN dataset showing the optimal k value

It can be observed from the above graph that the optimal number of k is somewhere between eight to ten. However, using more than five clusters resulted in very imbalanced clustering such that a few clusters contained only one record. The single member groups were detected as outliers and replaced with the mean values and the number of clusters was set to five. Although setting the number of clusters to five still produced imbalanced groups, each cluster had at least 20 records. The *k-mean++* clustering technique was performed multiple times on the URN data to get a good distribution of signals in clusters, the best obtained result is given in Table 7.1.

Table 7.1– The number of records in each cluster, after clustering URN signals with use of k-mean++ method

Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**
104	170	20	42	84

Unlike noise signals, which were available for each corresponding vibration measurement location, there is only one set of URN signals. It means we were not able to concatenate audio signals from different locations to create a big matrix. Instead, to estimate the level of URN signals, the machine learning algorithms were separately implemented on vibration data from each location of Queen of Oak Bay ferry with the use of the same labeled URN signals.

Accordingly, the dataset related to each location was divided into training and testing sets with the ratio of 70:30. This ratio is known for making the right balance in the trade-offs between generalizability and overfitting of trends to datasets. The Python scikit-learn toolbox was used to build the classifier and to test its prediction accuracy. To apply the Neural Network classifier, the division of data for training, validation, and testing was set to 70:15:15, and MATLAB's Neural Net Pattern Recognition application was utilized for this purpose.

In most cases, the Random Forest classifier outperformed Neural Network. This is likely due to the imbalance of classes having a greater impact on the sensitivity and robustness of the neural network, which is a parametric model. The result from the two classifiers in each location is given in Table 7.2.

Table 7.2 – Results from implementing two machine learning methods to classify vibration signals based on labeled URN signals. The highlighted column indicates the location that led to the best results

Classifier	**Accuracy at each location, %**								
	SG1	**SG2**	**PS1**	**PS2**	**ME1**	**ME2**	**GB1**	**GB2**	**Avg.**
Random Forest	88.8	85.7	84.8	85.2	89.5	86.2	86.9	87.1	86.8
Neural Network	82.9	75.2	80.7	81.4	84.8	84.5	81.2	83.1	81.7

From the table above, the Random Forest approach resulted in an average predictive accuracy of 86.8% and the Neural Network yielded an average predictive accuracy of 81.7%. The highest performance of models is related to ME1 location, where the accuracy of prediction is 84.8% with the use of Neural Net and 89.52% with the use of Random Forest algorithm. Figure 7-3 demonstrates the confusion matrix resulting from the Neural Network algorithm applied on ME1 dataset.

The performance of the developed model can be used as a benchmark for future studies. We have selected the Random Forest method which is sophisticated and known to perform well on a range of predictive model problems to evaluate the model on the problem and use the result as an approximate top-end benchmark. However, there might be a simpler model that achieves similar performance.

Achieving a relatively high accuracy in predicting URN level with use of patterns in vibration data verifies that there is a correlation between URN and vibration signals.

Based on these results, using the Kinetix vibration data it is possible to predict the level of URN caused by vibration with high accuracy.

Figure 7-3– The Confusion matrices resulted from the implementation of Neural Network algorithm on data using four attributes of the first 50 peaks of URN signals and four attributes of the first 25 peaks of vibration signals

Like the previous section, we tried to compare the level of URN to the level of vibration considering the labels that had been given to them. Unlike noise and vibration, there is not a consistent correlation between the intensity of URN clusters and the intensity of vibration clusters. This might be because of unknown factors impacting pressure fluctuation measured by hydrophone. Having more data at different speeds would help us better understand the correlation between the intensity of URN and vibration clusters. However, all URN measurements were obtained at a single point while keeping the same distance to the ferry, because of the difficulty associated with trying to keep pace or outpace the Queen of Oak Bay to obtain measurements along route at different speeds. Especially by looking at ship's speed data, Queen of Oak Bay ferry is usually on one of four states: At rest, acceleration, decelerating, or underway at constant speed. Figure 7-4 shows an example of eight hours of Queen of Oak Bay operating, where the underway condition is by far and away the most common. With this limiting factor, we were not able to relate vibration data to ship operating sensors with the current data set.

With regards to the on-board sensor data, the principal issue arises from the low sampling rate of Queen of Oak Bay's sensors, which report either the average or peak value for their parameters for a one-minute period, compared to several thousand times a second for noise, vibration, and URN. For example, the Queen of Oak Bay sensors may return a main engine operating RPM of 1200 for a given one-minute period, which does not reflect the reality that the system may be operating at a range of 1100 to 1300 RPM over that minute as the vessel overcomes wind and wave action to maintain a constant speed. Whilst it is possible to produce averages over a one-minute period for the recorded noise, vibration, and URN measurements, this has the same limitations as the one-minute average/maximum value data from the on-board sensor in that it is prone to obfuscating data.

For the signature parameters (i.e. URN), the main difficulty is that the vessel is only captured operating whilst underway. What this means is that there is little to no variation in operating parameters, as the ferry is simply transiting at maximum permissible speed. If we imagine this as a time-varying parameter, we see a near constant level of noise produced. Consequently, we do not accurately capture the *range* of possible efficiency states that the ferry is likely to operate under, so we cannot accurately gauge its' variation.

Whilst data was captured at both the Nanaimo and Vancouver ferry ports close to the Queen of Oak Bay's docking points using static hydrophones, the data obtained from these was not of sufficiently high quality for it to be included in the final assessments. The reason for this is twofold: firstly, because the hydrophones were unattended, we are not able to categorize other noise sources concurrent with the departure / arrival of Queen of Oak Bay (e.g. it is difficult to confirm what impact other ferries, commercial vessels etc.). Secondly, the tidal range and shallow nature of these measurement points means that there are physical limitations on the frequencies of sound which propagate out towards the hydrophone sensors.

Additional work with either ferry-mounted hydrophones, or more static measurement points along the Queen of Oak Bay's operating route, is required to produce this outcome as discussed below.

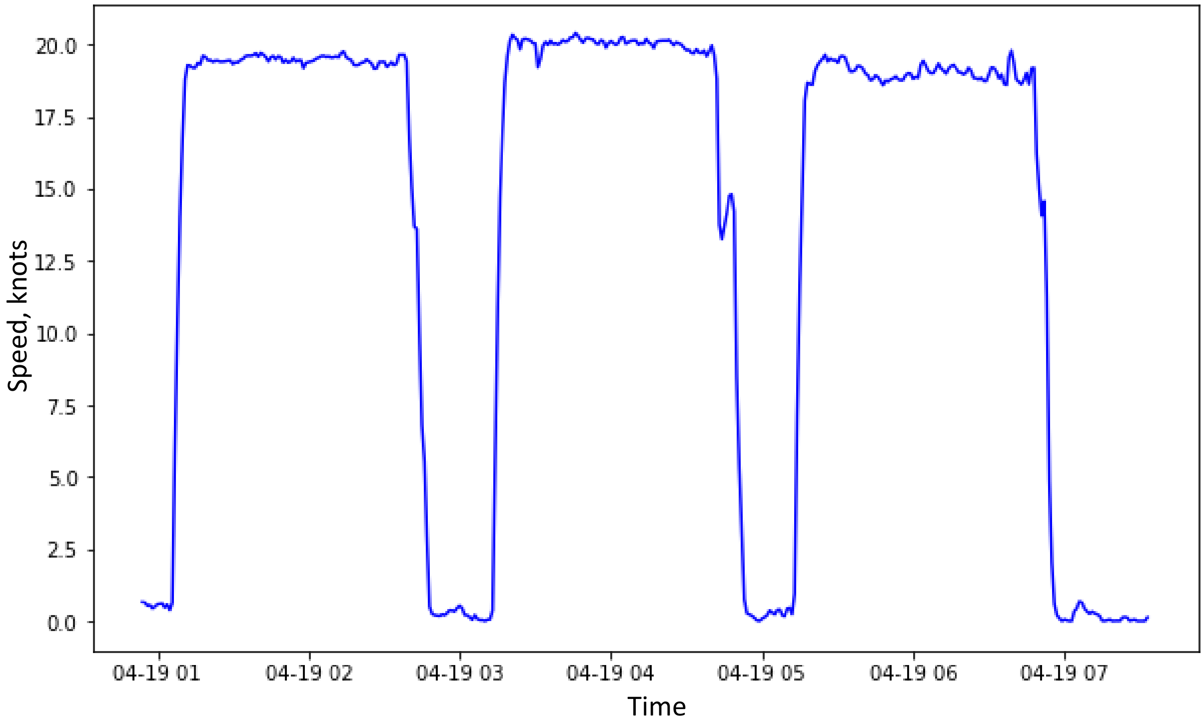


Figure 7-4 - An example of eight hours of the Queen of Oak Bay operating

8. Conclusions

The main objectives of this extensive body of work were:

1. Measure the relationships between URN and ship operating efficiency by correlating ship sensor data (including thrust, fuel efficiency, RPM, speed, and ship location) with hydrophone data and accelerometer data collected on Kinetix.

2. Quantify the relationship between URN and the above measurements so that URN can be directly estimated by dry onboard measurements.

3. Advance the Kinetix technology to a pre-commercialized state as a stand-alone onboard URN monitoring system for ships. At this stage of development, this could be paired with Allsalt Maritime's consulting services to deliver post-operational URN emissions reports.

4. Advance the Kinetix technology to a state where integration into ship bridge systems would be feasible, allowing development of real-time URN notifications to ship crews while the vessel is underway.

Conclusions pertaining to these objectives are given in the subsections below.

8.1. Relationships Between URN, Noise, Vibration, and Ship Sensor Measurements

The relationships between URN and ship operating efficiency were investigated in detail. The main finding was that it is likely to be practical to relate efficiency to URN but a modified approach will be required.

It was made clear at the start of the project that requiring the ferry to perform specific maneuvers outside of the regular transit, or attaching underwater cameras or a towed hydrophone array to the ferry, would be impractical.

This was not necessarily a problem as previous work on smaller craft had shown that it was possible to detect cavitation by comparing URN, speed and RPM in detail and looking for specific features at different speeds. The intention was to use this approach with the ferry, so relying on data analysis methods to compensate for the necessary limitation of the measured data.

The ship travels at a set speed for most of the transit, accelerating and decelerating close to the terminal. So, it was necessary to position the hydrophones close to the terminals to detect URN from the acceleration and deceleration phases, accepting that the data acquired would be more complex to interpret than a deep water measurement in mid channel.

The main issue was that the ship data is sampled slowly (once per minute). The ship can travel a significant distance at different RPM and speed between samples. The hydrophones sample very fast (thousands of samples per second) but were at fixed and acoustically noisy locations where the ship moves past them reasonably quickly. Given the different sampling resolutions, picking out the relevant URN/speed/RPM trends was found to be impractical. There were simply not enough data points measured on the ship as the ship was passing the hydrophone.

There are two promising ways forward on this issue as discussed later under future work.

The first is to use the knowledge gained from the present project to optimize the hydrophone locations to maximize the quantity and quality of ship and hydrophone data during acceleration and deceleration phases.

The second is to use the large volumes of data obtained for this project to 'baseline' the relationship between the ferry machinery and systems and the on-board machinery vibration measurements. This could then be monitored over time to look for variations due to wear or other machinery issues. Given that the present project found a strong relationship between measured vibration and URN, a more detailed understanding of the relationship between the ferry machinery and the dry side vibration measurements would also provide information on the long-term variation in URN emission.

Both approaches, if found to be practical with the BC ferries trials vessel, would be applicable to other vessels of various types and sizes operating in Canadian waters.

8.2. Estimating URN from Noise and Vibration Measurements

The findings outlined in Section 7, couched in machine learning terms as they are, benefit from further explanation. The principal task of a machine learning algorithm is to look at a data set and decide based on that data set as to how to automatically group data based on a set of characteristics. Let us set up a hypothetical example to explain this further.

Imagine we take vibration measurements and describe them by two simple parameters: "Magnitude" and "Dominant Frequency", and we create two labels for the data: "Engines on" and "Engines off". We can assume, based on our understanding of vibration, that the Magnitude and Dominant Frequency are going to be grouped differently in the two conditions, as shown in Figure 8-1. In this example, we can see two very clear and distinct groups that it is trivial to draw groupings around to arrive at an automatic labelling system, represented by the colored ovoid shapes in Figure 8-1.

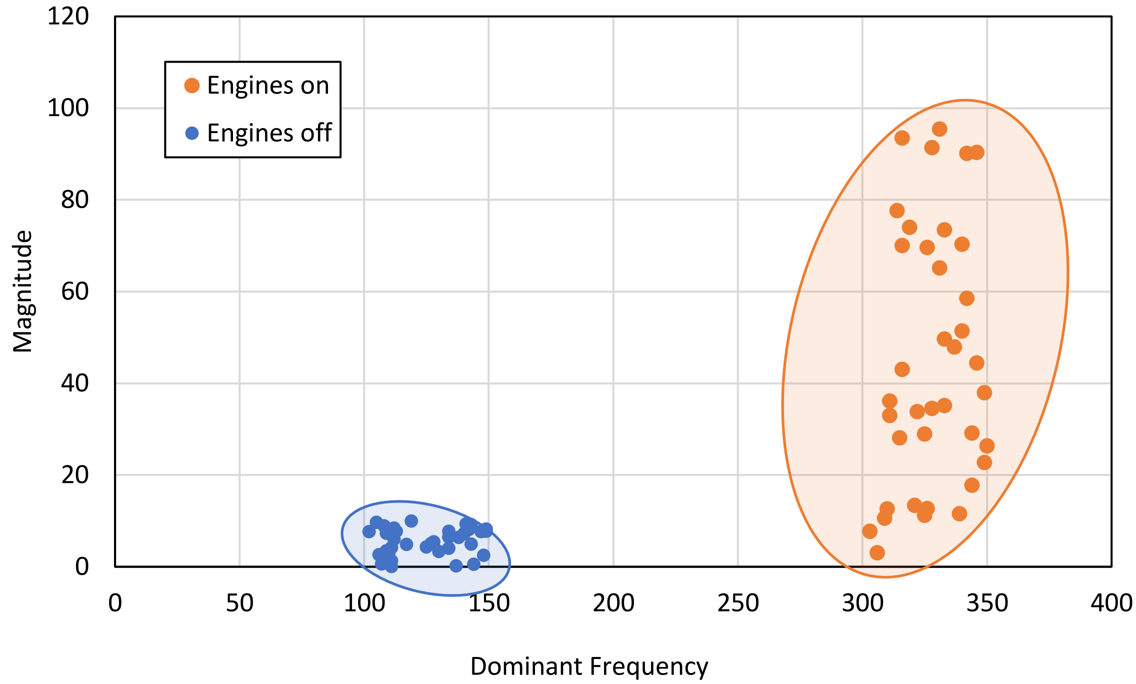


Figure 8-1 - Example grouping for hypothetical vibration measurements. Groupings into "Engines on" and "Engines off" labels are indicated by colored ovoid.

This is what is referred to as a "supervised" machine learning, as we know broadly what the categories are ahead of time and can apply some simple logic to the data. In many instances of machine learning applications, we instead want to determine these labels automatically, and often have many more axes along which data can be categorized.

The data in the current project was fed into the machine learning algorithm using two different parameterizations; the first fifty peaks in frequency, and the first twenty-five peaks in both vibration and URN, with each peak being described by four parameters. These five groups correspond to effective "magnitude" levels of the measurements (where magnitude should be taken to mean "relative size of measurement compared to other measurements" and not to be a specific vibration/noise level with a measurement unit attached. Each of these groups is labelled 1 through 5 for both URN and vibration measurements, and we can then think of the relationship between the two physical characteristics like so: "***A magnitude change in Label 1 in the vibration measurements is typically correlated with a change in magnitude change in Label 1 in the URN measurements***" – i.e. the magnitudes of both groups, across the 25 parameters used to describe each measurement period, are highly correlated.

This outcome should be viewed as a strong first step in deriving operating parameters for the Queen of Oak Bay which minimize its noise profile for the purposes of protecting marine life, and in predicting when vessel operations are likely to disturb or injure marine mammals.

8.3. Advancing the Kinetix technology for a pre-commercialized state, and integration into ship bridge systems

The final phase of this project, which proved a strong correlation between the URN and vibration measurements, functions as an effective proof of concept that the Kinetix system is a viable option for on-board URN / machinery monitoring system. Before any consideration can be given to a deployable product, we must first establish proof of concept – i.e. can we prove that the equipment itself is able to make the measurements and assessments required to even consider further development. The results given in the previous section are proof that the measurements made by the Kinetix system can be used to make predictions about URN signal magnitude, and we have effective proof of concept. However, the machine learning algorithm, because of the data fed into it, lacks the level and accuracy of predictive power that would be required to produce a pre-commercial-state piece of hardware. The roadmap for what development to a pre-commercialized state is, broadly, as follows:

1. Increase the operating range over which the machine learning model is trained
2. Adapt ML model to work with typical broadband metrics used in legislation etc
3. Add on-board real-time or close-to-real time machine learning algorithm capacity to Kinetix hardware
4. Investigate wireless, local display, or cable-routing options for display purposes.

The Kinetix architecture is also already compatible with COTS and custom display systems, in either a wired or Bluetooth format. This puts us in a strong position to begin discussions around what an integrated system may look like for platforms like Queen of Oak Bay, and what outputs are useful for maintenance and operational personnel at BC Ferries and Transport Canada.

9. Potential Future Work

The following subsections detail ways in which the current body of work could be expanded to improve upon the findings of this project and move us towards a fully-fledged URN and machinery vibration monitoring system for deployment on platforms like the Queen of Oak Bay.

9.1. Hydrophone Measurements of Cavitation Onset

One of the key noise sources identified as a risk to marine mammals at the outset of the project, and one which also has strong operational efficiency and machinery maintenance/life-cycle implications was propeller cavitation. Propeller cavitation is caused by pressure at the surface or edge of the propeller blade becoming high enough to force bubbles of water vapor to form. This is a high-energy event which produces a lot of noise and can, over time, produce pitting on the surface of the propeller, leading to a reduced life cycle and reduced efficiency. It was hoped that underwater noise measurements, combined with information relating to propeller operating speed, would allow us to identify cavitation events. However, due to the limitations in how URN was measured, there is insufficient data to allow us to correctly identify the onset of cavitation. Specifically, the Queen of Oak Bay was only measured whilst operating at typical cruise speeds in deeper water and whilst it is likely that cavitation occurred during this period, we cannot say specifically at what points cavitation occurred without closer inspection.

Previous work has used underwater cameras focused on boat propellers to visually identify the onset of cavitation and link this to increases in energy at specific frequencies and engine speeds. Without cameras, or the ability to carry out controlled trials with specific engine speeds in the vicinity of the hydrophone, or some other method of confirming the presence of cavitation, it will not be possible to include the onset of cavitation and the resultant noise from this in any predictive model.

Future work could look to bridge this gap in understanding by measuring at different locations which capture the full range of operating speeds and conditions, with the transition from Departure Bay to the open water in the Strait of Georgia being a good candidate for this location.

9.2. Establishment of an Operational Baseline for Queen of Oak Bay for Condition Monitoring

One of the unforeseen outcomes of this project is the sheer volume of data obtained. The total volume of vibration, noise, and URN data is in the order of several hundred gigabytes, and the vibration data in particular spans weeks of continuous operation due to the high storage and power capacity of the Kinetix systems. It is Allsalt Maritime's view that this data, rather than being superfluous to requirements, presents a unique opportunity for Transport Canada and BC Ferries.

If we operate under the assumption that the Queen of Oak Bay was operating as intended, with no damage to machinery and everything operating under normal conditions, then what we have recorded is an historic baseline for standard operation across the entire operational profile of the ferry. Continuous monitoring of vibration in key machinery spaces, and comparison with this operating baseline presents the opportunity to identify early variation from this baseline and flag to operators that maintenance may be required. Whilst this is outside the scope of the current project, we believe that this would be a valuable outcome for future projects associated with the Queen of Oak Bay.

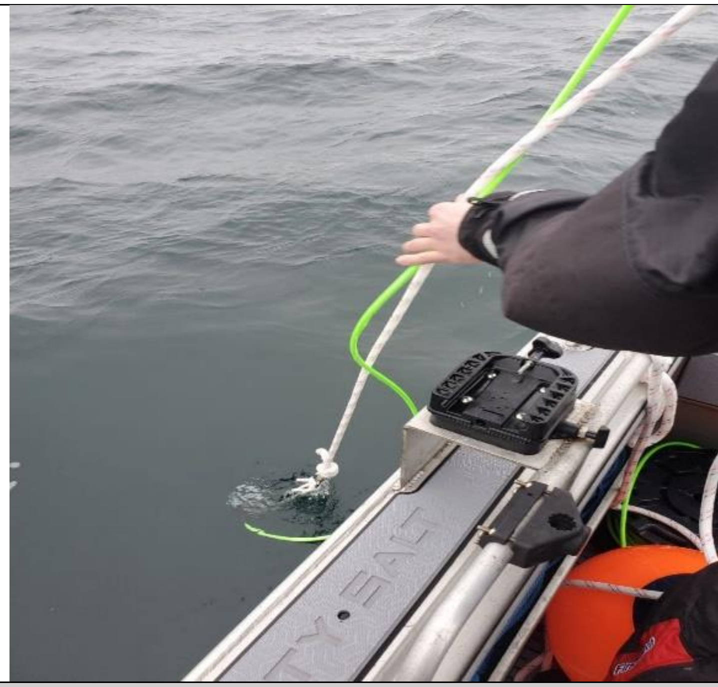
The present project found a strong relationship between measured vibration and URN, so a more detailed understanding of the relationship between the ferry machinery and the dry side vibration measurements would also provide information on the long-term variation in URN emission.

9.3. Broadband URN Prediction

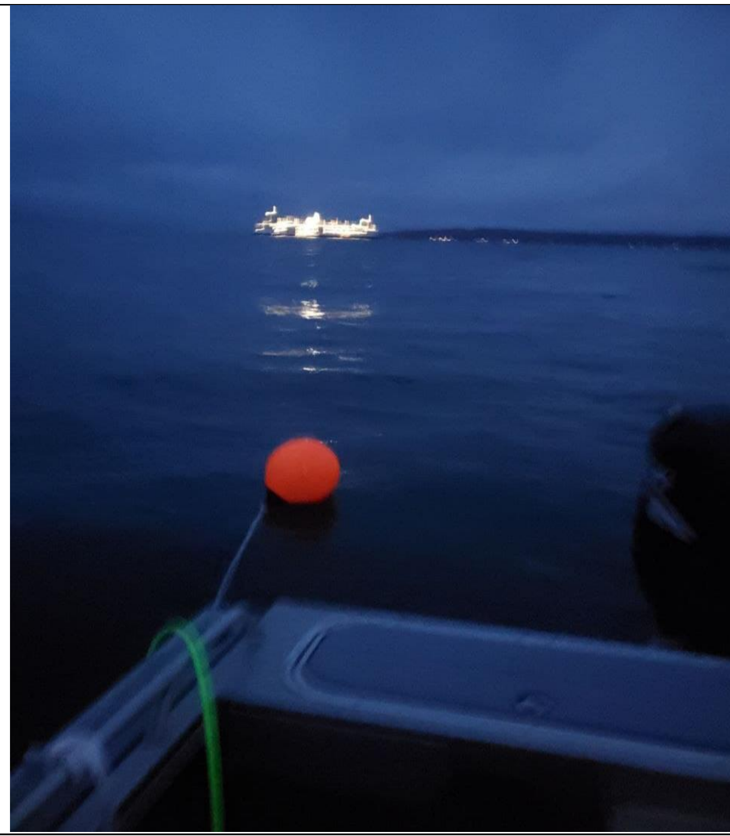
To bridge the gap between the current narrowband analysis and more practical measures of noise exposure, it will be necessary to conduct additional underwater noise measurements which focus on obtaining both narrowband and broadband measurements. This will allow us to move from a two-phase model (narrowband vibration → narrowband URN) to a three-phase model (narrowband vibration → narrowband URN → broadband URN). This, coupled with an understanding of what marine life is at risk of noise exposure, will allow operators to identify machinery which produces specific tones, which contribute to energy bands at which specific classes of marine mammal are at risk. This in turn allows them to set operational parameters which minimize risk for injury or displacement of marine mammals because of the operation of Queen of Oak Bay.

APPENDIX A – En Route Measurement Data Recording Log

Measurement #1		
Hydrophone ID	6302	
Date	2022-01-04	
Ferry position	departure from Nanaimo terminal	
Depth of water	500 ft	
Hydrophone cable	4 m	
Event	Time	Approx. Distance to the ferry
start	8:34	1.5 km
closest distance	8:42	200 m
stop	8:50	1.5 km
Other events		
aircraft sound	8:35	
aircraft sound	8:47	

Measurement #2		
Hydrophone ID	6302	
Date	2022-01-04	
Ferry position	entering to the terminal	
Depth of water	520 ft	
Hydrophone cable	4 m	
Event	**Time**	**Approx. Distance to the ferry**
start	11:55	2 km
closest distance	12:06	150 m
stop	12:11	1 km
Other events		
another ferry passed	11:57	
approx. distance recorded	12:00	1 km
approx. distance recorded	12:04	400 m

Measurement #3		
Hydrophone ID	6302	
Date	2022-01-04	
Ferry position	departure from Nanaimo terminal	
Depth of water	500 ft	
Hydrophone cable	4 m	
Event	**Time**	**Approx. Distance to the ferry**
start	13:04	1.5-2 km
closest distance	13:13	200 m
stop	13:16	1 km
Other events		
another ferry is close	13:04	
approx. distance recorded	13:10	600 m
aircraft sound	13:12	

<table>
<tr><td colspan="2">Measurement #4</td><td rowspan="6"></td></tr>
<tr><td>Hydrophone ID</td><td>6302</td></tr>
<tr><td>Date</td><td>2022-01-04</td></tr>
<tr><td>Ferry position</td><td>entering to the terminal</td></tr>
<tr><td>Depth of water</td><td>530 ft</td></tr>
<tr><td>Hydrophone cable</td><td>3-4 m</td></tr>
<tr><td>Event</td><td>Time</td><td>Approx. Distance to the ferry</td></tr>
<tr><td>start</td><td>17:04</td><td>2 km</td></tr>
<tr><td>closest distance</td><td>17:10</td><td>150 m</td></tr>
<tr><td>stop</td><td>17:16</td><td>1.5 km</td></tr>
<tr><td colspan="3">Other events</td></tr>
<tr><td>approx. distance recorded</td><td>17:08</td><td>500 m</td></tr>
</table>

Measurement #5		
Hydrophone ID	6302	
Date	2022-01-04	
Ferry position	departure from Nanaimo terminal	
Depth of water	530 ft	
Hydrophone cable	3-4 m	
Event	Time	Approx. Distance to the ferry
start	18:05	1 km
closest distance	18:10	300 m
stop	18:15	1 km

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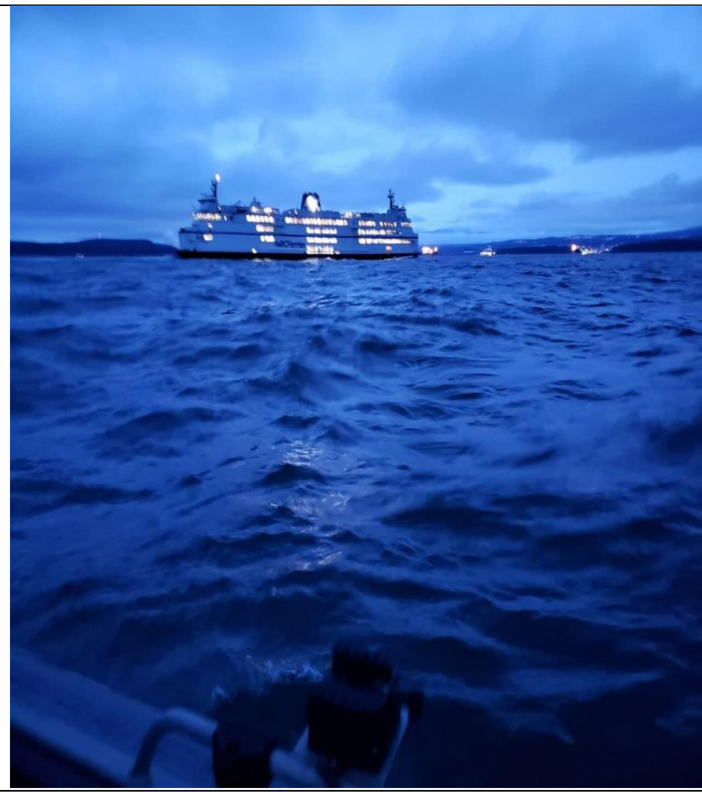
Measurement #6		
Hydrophone ID	6302	
Date	2022-01-05	
Ferry position	entering to the terminal	
Depth of water	435 ft	
Hydrophone cable	3-4 m	
Event	Time	Approx. Distance to the ferry
start	7:44	500 m
closest distance	7:46	100 m
stop	7:58	3 km
Other events		
approx. distance recorded	7:49	1 km

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Measurement #7	
Hydrophone ID	6302
Date	2022-01-05
Ferry position	departure from Nanaimo terminal
Depth of water	435 ft
Hydrophone cable	3-4 m

Event	Time	Approx. Distance to the ferry
start	8:24	3 km
closest distance	8:39	300 m
stop	8:50	2 km
Other events		
approx. distance recorded	8:35	1 km
approx. distance recorded	8:44	1.5 km