Mitigation of Radiated Noise of Small Marine Craft using Condition Based Monitoring Final Report

Report for: Transport Canada – Quiet Vessel Initiative (QVI)

Name of client: Transport Canada

Report no.: TR-24-18

Project no.: PRJ11100379887

Revision no.: 0

22 March 2024

Summary

Mitigation of Radiated Noise of Small Marine Craft using Condition Based Monitoring Final Report

Project Number: PRJ11100379887

Authors: A. Deeb, C. Boudreau, K. MacKay

Security classification of this Report: Distribute only after client's acceptance

Report no.:	Revision no.:	Report date:
TR-24-18	0	22 March 2024
Prepared by:	**Reviewed by:**	**Approved by:**
Amy Deeb Intermediate Engineer	Ken MacKay Sr. Engineer	Dave Whitehouse Technical Manager

Registered name:	Martec Limited
Correspondence address:	Lloyd’s Register Applied Technology Group 237 Brownlow Ave, Suite 200 Dartmouth, NS B3B 2C7
Contact:	Key MacKay T: 902 880 4098 E: Ken.MacKay@lr.org

Martec Limited is a member of the Lloyd’s Register Group, doing business as the Applied Technology Group

Client name and address:
Transport Canada
330 Sparks Street, Place de Ville,
Tower C
Ottawa ON K1A 0N5

Client contact:
Ali Faramarzifar
T: (289) 219-1853
E: Ali.Faramarzifar@tc.gc.ca

Document control

Revision history

Revision No.	Date	Revision
0.0	03/22/2024	Initial release of final report
1.0		
2.0		

Proprietary Notice

This report was prepared under Contribution Agreement No. 164607 “AGREEMENT FOR MITIGATION OF RADIATED NOISE OF SMALL MARINE CRAFT USING CONDITION-BASED MONITORING” between Transport Canada and Martec Limited. The project is funded through the Quiet Vessel Initiative under the Program To Address Disturbances From Vessel Traffic.

The information contained herein may be used by Transport Canada for their purposes only.

Complete use and disclosure limitations are contained in Contribution Agreement No. 164607.

Executive summary

This project was funded under the Transport Canada Quiet Vessel Initiative and spanned two fiscal years (Fall 2022 – March of 2024). The purpose of this project is to provide decision support to reduce the underwater radiated noise (URN) of a small marine craft. The project aims to develop a methodology to analyze the URN of a class of small marine craft in order to generate a transfer function (TF) that relates on-board measures of structure-borne noise to the resulting URN spectrum. This class URN TF is the core of a CBM sensor package for small marine craft to provide information to enable a vessel operator to monitor their vessel's URN, and, when possible, take actions to reduce the URN emissions. The proposed approach is known as condition-based monitoring (CBM), in which measures of a vessel's state or condition are used to monitor its performance and predict when maintenance is needed. Specifically, the goal of this project was to design a cost-effective instrumentation package and class URN TF to inform a vessel operator of the vessel's current URN levels based only on measures that are available onboard the vessel. This project focused on Cape Islander fishing vessels due to their popularity and relative structural and mechanical simplicity.

Given these requirements, we identified options for simple and inexpensive components to make up the CBM instrumentation package. The resulting system consisted primarily of a Raspberry Pi 4 Model B as the computer, a 4-20 mA accelerometer, a Pi-SPi-8AI Raspberry Pi Analog Input Interface board as the DAQ, and a Honeywell Hall-effect Sensor to measure RPM. In total, the cost of this instrumentation package is under $500 CAD. This cost is based on ordering only enough components for one package, thus lacking any efficiencies of scale. A prototype CBM instrumentation package with user interface was developed and field tested.

The use of such components for a CBM system on small marine craft to predict URN in-situ is not well established. As a result, a trial plan was developed to record data from fishing vessels using both the prototype instrumentation package as well as the more traditional instrumentation package used in the previous project's trials to be able to compare the performance using data collected under each system. Trials were completed using the CBM system using 4 small marine craft (Cape Islanders) in September-October 2023. The trial data was processed to evaluate and refine the CBM system.

This project shows that a small number of sensors can predict the URN for a Cape Islander with acceptable performance (~ 5.1 dB error). The minimal sensor package comprised only two sensors: one accelerometer located on the hull above the propeller providing the RMS velocity for vibration level between 10 and 100 Hz, and a tachometer measuring the shaft RPM. The URN predictor also required the current season (calculated from the date), the year the vessel was built, and the engine horsepower as input.

The inability to apply the model learned on 2020/2021 records from a previous project to the 2023 trials indicates that data used to train the model must be obtained using consistent measurement methods. The use of data record separation techniques other than by general randomization for training and testing was shown to increase the error in the predicted URN for the Cape Islander class. The sensitivity of the data separation approach suggests that there is a lot of variation within the class of Cape Islanders and that a large sampling of Cape Islanders would need to be included in the training data set before the model can generalize to other members of the Cape Islander class without including their URN records in the model training.

Contents

List of Figures

List of Tables

List of Abbreviations

ADC	Analog to Digital Converter
CBM	Condition-Based Monitoring
DAQ	Data Acquisition System
GIT	Graphite Innovation and Technologies
GPS	Global Positioning System
GUI	Graphical User Interface
HP	Horsepower
IEPE	Integrated Electronics Piezo-Electric
LAN	Local Area Network
LOA	Length Over All
LR	Lloyd’s Register
ML	Machine Learning
NI	National Instruments
NSTM	Naval Ships’ Technical Manual (Metric for fouling on hull)
PLC	Programmable Logic Controller
RMS	Root Mean Square
RPM	Rotations Per Minute
SBC	Single-Board Computer
SOG	Speed Over Ground
STW	Speed Through Water
TC	Transport Canada
TF	Transfer Function
URN	Underwater Radiated Noise

1. Introduction

The purpose of this project is to provide decision support to reduce the underwater radiated noise (URN) of a small marine craft. The project aims to develop a methodology to analyze the URN of a class of small marine craft in order to generate a transfer function (TF) that relates on-board measures of structure-borne noise to the resulting URN spectrum. This class URN TF will be the core of a CBM sensor package for small marine craft to provide information to enable a vessel operator to monitor their vessel's URN, and, when possible, take actions to reduce the URN emissions. The proposed approach is known as condition-based monitoring (CBM), in which measures of a vessel's state or condition are used to monitor its performance and predict when maintenance is needed. Specifically, the goal of this this project is to design a cost-effective instrumentation package and class URN TF to inform a vessel operator of the vessel's current URN levels based only on measures that are available onboard the vessel.

The priority of this project is placed on small marine craft – specifically fishing vessels known as Cape Islanders (shown in Figure 1-1) – for two reasons. First, there are over 3500 Cape Islanders in Nova Scotia so insight of this type can have a wide impact for vessels that do not otherwise have data related to their URN emissions. Second, Cape Islanders have a simple structure with minimal machinery, which makes them an effective test case to demonstrate the potential for our proposed CBM approach.

Figure 1-1 Example of the class of small marine craft known as Cape Islanders

Cape Islanders are used for various activities in New Brunswick, Nova Scotia, and Prince Edward Island including lobster and halibut fishing, tagging sea turtles, deep sea fishing tourism, and as charters for research activities. The Cape Island style of boat has been built since the 1970s so many have undergone refits to broaden or lengthen their hulls. They are typically fibreglass with wooden frames, 10-13 m long, 4-6 m beam, and have a draft of approximately 1.5 m. Most of the operators we have spoken with claim a maximum speed around 10 knots, typically using a 4-stroke, 200-300 HP diesel engine. Propellers are not consistent across Cape Islanders, but the most common propellers available are 4-bladed.

As with all vessels, URN produced by Cape Islanders comprises three categories: structure-borne noise, flow or hull hydrodynamic noise, and propeller noise. Structure-borne noise arises from mechanical systems whose vibrations excite the structure of the boat. Those vibrations are transmitted through the hull into the water. In general, travelling at faster speeds requires higher engine RPM, which produces more intense vibration, and louder sound in the water. For small marine craft, the diesel engine is the only mechanical system onboard that is in operation while the vessel is underway. Flow noise arises from the sound of the water moving along the hull. Faster speeds and rougher surfaces result in more flow noise. For small marine craft, fouling on the hull can cause some hull noise, but this type of noise is much quieter than the other two categories. Propeller cavitation noise is a significant feature in a small marine craft's URN signature. At low speeds, cavitation is minimal and structure-borne noise dominates the vessel's URN. As the speed increases, cavitation dominates the URN, especially in the mid to high frequencies. For the Cape Islanders we worked with, their propellers are not ideally sized for their operations, so they operate in the cavitation dominated region when underway.

This project was funded the Transport Canada Quiet Vessel Initiative and builds on prior work undertaken by LR and GIT on a separate project. The work spanned two fiscal years (Fall 2022 – March 2024).

After an overview of the proposed CBM system, the work to develop a URN TF that applies to the Cape Islander class is detailed. This work defines the minimum requirements for the instrumentation package for the CBM system. The trial plan is described for conducting trials in September-October 2023. Next the instrumentation package for the prototype CBM system is described and the assessment of the URN TF for the Cape Islander class of vessels given before finally concluding with recommendations.

2. CBM System Overview

The proposed CBM system comprises both software and hardware components as shown in Figure 2-1.

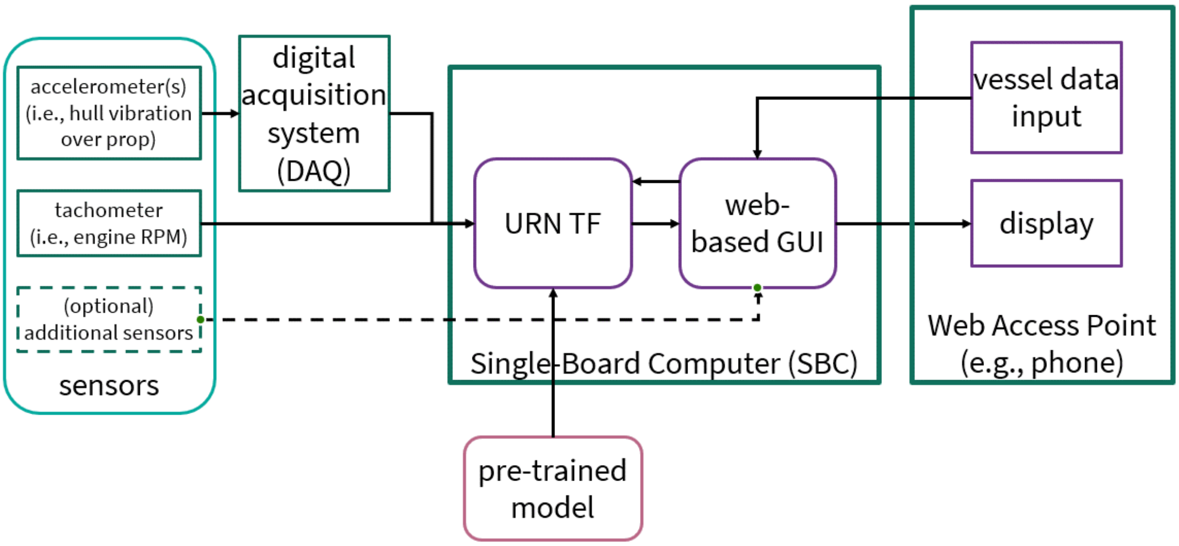

Figure 2-1 CBM System Overview

At the core of the CBM software is a class URN TF which is discussed in Section 4. In broad strokes, it is trained (i.e., the parameters of the TF are determined) offline using data from a small number of representative class members, then used in-situ to calculate the URN decidecade spectrum based on current sensor measurements.

On the hardware side, the components can be divided into three groups: the sensors, the data acquisition and processing system (in this case a single-board computer (SBC)), and a web access point such as a phone or laptop through which the operator can view and interact with the CBM system. The instrumentation package (i.e., sensors, data acquisition, SBC) is described in Section 5.

SBCs with ethernet/Wi-Fi connectivity are capable of hosting web applications accessible via Local Area Network (LAN), that could serve as a user interface for vessel parameter input, and sensor measurement and URN prediction display. Such web applications would be accessible through any device connected to the SBCs LAN – such as a laptop connected to the same router as the SBC via ethernet, or a smart phone connected directly to a Wi-Fi Network transmitted by the SBC itself.

The above describes the minimum viable CBM system for a small vessel interested in their URN signature. Including additional sensors may improve an operator's understanding of their vessel's condition. For example, if the vessel speed is recorded using GPS, the operator can be alerted if there is an unexpected change in the relationship between speed and RPM (e.g., if the RPM required to achieve a particular speed is persistently larger than normal without adverse weather conditions, this could imply that engine maintenance is required. Such extensions to the sensor package are not required to achieve the primary goal but could be considered if they are not too costly.

3. Trial Method and Data Collection

Trials were conducted to collect data with the prototype CBM system and measure the URN of fishing vessels underway in September and October 2023. Four boats were selected – three from the previous project and one vessel not part of the previous project. The particulars of the four boats can be found in Table 3-1.

The trials were performed near the fishers' home port (McGrath's Cove) for convenience. The trial site location (44° 27.2' N, 63° 55.4' W) consisted of a flat sandy bottom with a depth of approximately 50 m (Figure 3-1). Two vessels were in use on each trial day – one is the vessel under test (having its URN recorded in different operating states), and the other is a support vessel serving as a platform from which to put two hydrophones into the water column. The arrangement of the boats and the hydrophones are depicted in Figure 3-2. The boats switched roles during the day once the trial on the first boat was completed so that both vessels are tested that day. The order of events on each trial day is listed in Table 3-2. The boat hulls were cleaned prior to the trials to remove fouling.

For efficiency, the trials were carried out to record the necessary data for this project as well as for another TC QVI project on the topic of URN from propeller cages (QUANTIFYING UNDERWATER RADIATED NOISE (URN) EFFECTS OF PROPELLER CAGES). Each vessel thus underwent three days of tests: one without a cage, one with the cage, and one with a fouled cage. In total, the trial consists of six measurement days and four vessels. A list of the trials conducted is given in Table 3-3.

Fouling of the propellor cages was accomplished by blocking a section of the cage to reduce flow through a section of the cage. A rectangular section of sheet metal was attached to both sides of the cage towards the leading edge of the cage and at approximately the same elevation as the shaft line. Figure 3-3 shows an example of the attached fouling. It should be noted that the fishers reported that the cages do not typically foul by growth of barnacles and other marine life, but rather fouling of the cages occurs when seaweed or other material becomes entangled in the cage. The fouling applied to the cages for the trial was an attempt to mimic the fouling experienced by the fishers.

Table 3-1 General boat information

Boat	Year Built	Displacement (short tons)	Draft (ft)	LOA (ft)	Beam (ft)	Engine	HP	Gear box reduction
Brooklyn and Boys	2001	6.1	3.3	34	12	Ford Lehman Senator	165	2:1
Bay Bliss	1993	11.5*	4.0	35.0	13	471 Detroit Diesel	160	2.45:1
Just Once	1985	11.5*	3.5	37.0	16	Caterpillar 3208 YR 1996	210	2.5
This Is It	1982	14.2	3.5	34.1	18	Caterpillar C7	251	2.5:1 Twin Disk

* Estimated

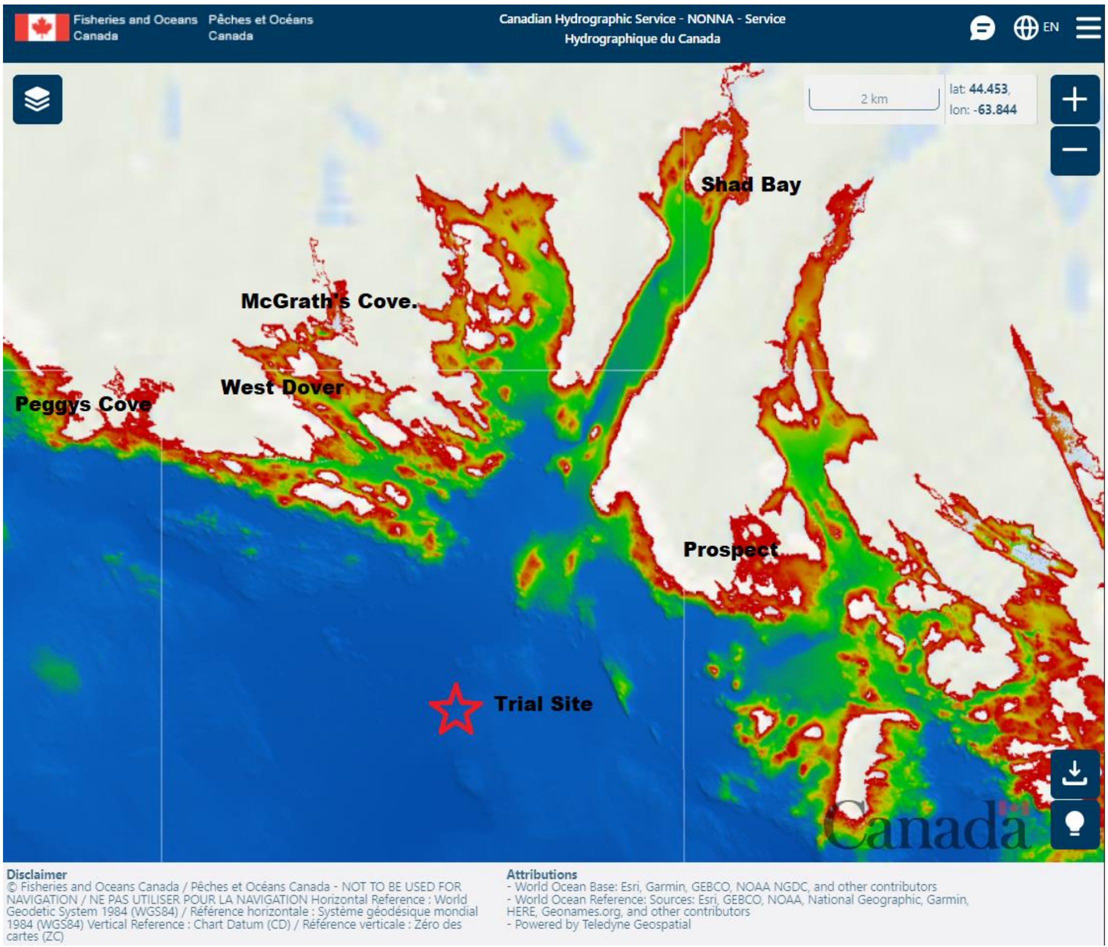

Figure 3-1 Trial Site Location

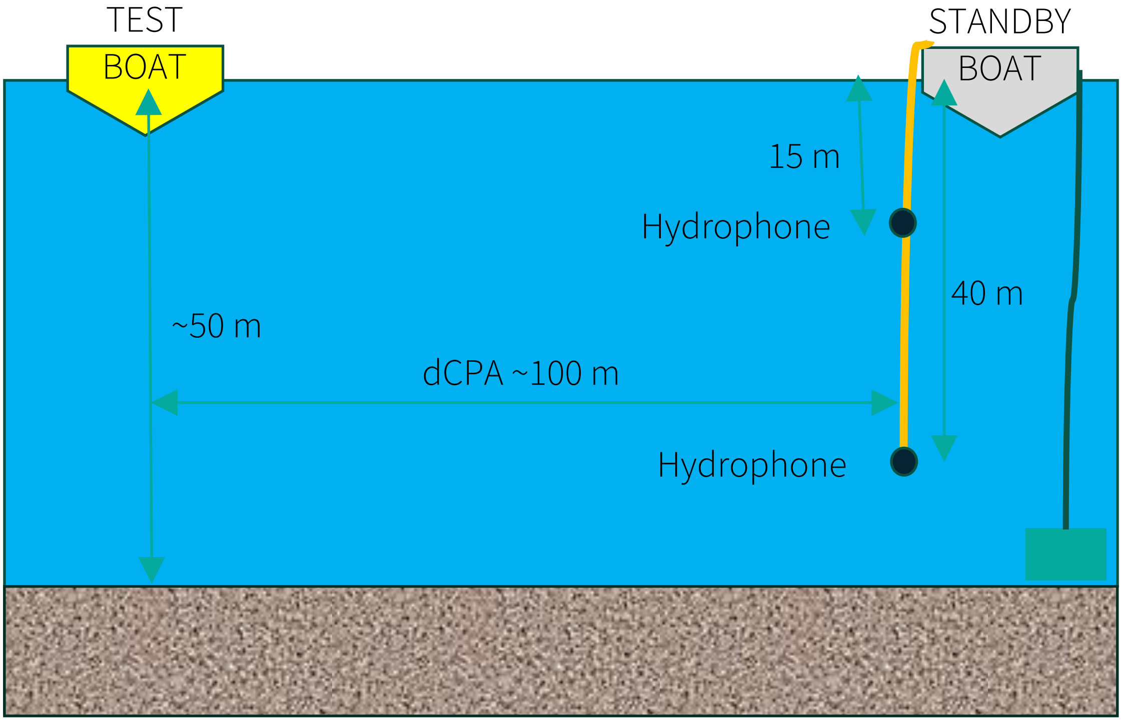

Figure 3-2 Arrangement for URN measurements.

Table 3-2 Order of events on each trial day

Order	Event
1	Arrive at wharf
2	Load CBM and PSARAS equipment onto boats (test and support)
3	Install CBM and PSARAS equipment on boats
4	Transit to test site, anchor support boat, test boat moves off ~100 m
5	Measure Ambient
6	Static Runs
7	Dynamic Runs
8	Measure Ambient
9	Uninstall equipment from each boat,
10	Return to wharf (if wave condition is too high for safe transfer at test site)
11	Transfer equipment between test and support boats
12	Install equipment on boats
13	Transit to test site, anchor support boat, test boat moves off ~100 m
14	Measure Ambient
15	Static Runs
16	Dynamic Runs
17	Measure Ambient

Order	Event
18	Transit back to wharf
19	Uninstall, pack up equipment
20	Depart wharf

Table 3-3 Summary of trials (boat hull configuration and performed runs)

Boat	Date	Trial number	Cage	Static Runs (RPM)	Dynamic Runs (knots)
Just Once	9/13/2023	HS3020	No	750, 1000, 1200, 1400, 1600	4, 6, 8, 9
Just Once	9/21/2023	HS3022	Yes	750, 1000, 1200, 1400, 1600	4, 6, 8, 9
Just Once	9/25/2023	HS3025	Fouled	750, 1000, 1200, 1400, 1600	4, 6, 7, 8
This Is It	9/13/2023	HS3021	No	850, 1050, 1250, 1500, 1750	4, 6, 8, 9
This Is It	9/21/2023	HS3023	Yes	850, 1050, 1250, 1500, 1750	4, 6, 8, 9
This Is It	9/25/2023	HS3026	Fouled	850, 1050, 1250, 1500, 1750	4, 6, 7, 8
Bay Bliss	10/12/2023	HS3028	No	600, 700, 1000, 1200, 1600	4, 6, 8, 9
Bay Bliss	10/17/2023	HS3029	Yes	600, 1000, 1200, 1600, 2000	4, 6, 8, 9
Bay Bliss	10/19/2023	HS3032	Fouled	600, 1000, 1200, 1600, 2000	4, 6, 8, 9
Brooklyn And Boys	10/12/2023	HS3027	No	700, 1000, 1200, 1600, 2000	4.5, 6, 8, 9
Brooklyn And Boys	10/17/2023	HS3030	Yes	750, 1000, 1200, 1600, 2000	4, 6, 8, 9
Brooklyn And Boys	10/19/2023	HS3031	Fouled	750, 1000, 1200, 1600, 2000	4, 6, 8, 9

Figure 3-3 An example of artifially fouling the cages by means of a metal plate.

Each trial consisted of a number of measurements for a given boat configuration consisting of ambient measurements, static runs, and dynamic runs. Ambient measurements comprise both vessels shutting off their engines (and any other vibratory equipment) such that the background noise at the site can be recorded for 30 seconds. Static measurements comprise the vessel under test operating with the propeller out of gear at 4 or 5 different engine RPM setpoints. Both vessels remain approximately stationary during the static measurements except for drifting due to any wind, waves, tides or current. For dynamic measurements, the boats travel a straight line passing the hydrophones (support boat) at a nominally constant speed. Figure 3-4 shows the schematic for the dynamic URN tests. Dynamic measurements are made at 4 or 5 different speeds, with two runs completed at each speed on reciprocal headings.

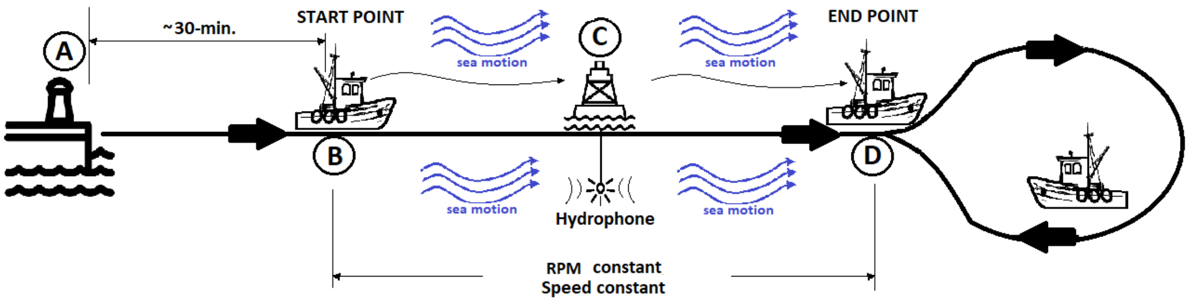

Figure 3-4 Circuit for recording URN measurements

The equipment used in the trials for the CBM project are:

- PSARAS (Portable Ship Ranging Analysis System) to record URN.
    - Sensors: 1 GPS receiver on the support boat, 2 GPS receivers on the boat under test, 1 radio antenna per boat, 2 hydrophones.
    - Hardware and software to enable tracking the position of the boat under test and recording the corresponding URN.

- Martec IR Tachometer and IEPE Accelerometers, laptop, and NI DAQ to provide comparison for CBM Prototype Instrumentation Package.
- CBM Prototype Instrumentation Package, as described in Section 5.

In addition to the URN, the following variables were observed during the trials:

- Date, time.
- Engine characteristics: engine HP, number of strokes, whether turbocharged, gear ratio.
- Vessel characteristics: beam, length overall, draft, dry weight (tons), year built.
- Weather (estimated by fisher / hindcast): wind speed, temperature, wave height.
- Vessel state: number of passengers, cage presence/fouling, approximate cleanliness state (recently scraped, newly coated, fouled, etc.).
- Run measures: Engine RPM, vibration on the hull at a position over the propeller, vibration at the engine foundation.
- For the propellor cage project, an IEPE pressure sensor (PCB model 113B28 or 113BB26) was installed on the hull near the propeller for each trial. The pressure sensor was fitted in a mount that was fixed to the hull using the outer bolt used to secure the cage, which put the sensor just outboard and slightly aft of the propellor (Figure 3-5 Pressure sensor mounted on the hull near the propellor.Figure 3-5). The position of the sensor location was recorded for each boat. The pressure data was recorded using the NI DAQ device that was also used to record the hull vibration.

(

Figure 3-5 Pressure sensor mounted on the hull near the propellor.

4. Class Underwater Radiated Noise Transfer Function

The purpose of a URN transfer function (TF) is to relate measurements available on-board a vessel to the underwater noise the vessel generates. This includes propeller cavitation noise, machinery noise, and flow noise (ordered according to their level of contribution from high to low in general). Typically, the URN TF must be studied for each specific vessel's configuration as variations in equipment, loading and even the individual operator can have significant impacts on a vessel's URN signature. However, small marine craft such as those in Canada's inshore fishing fleet, have simple designs that are expected to result in consistency between individual vessels. As a result, we propose to perform a class-wide analysis to establish a class URN TF for small marine craft.

Developing such a TF appears amenable to a data-driven treatment since a machine learning (ML) approach (i) captures the many conditions that affect a vessel URN, and their sometimes opaque inter-relationships; (ii) takes advantage of the large volumes of URN measurements made in each instance of a ranging, and (iii) the burden of diverse data sources is reduced due to the hypothesized smaller diversity within a small vessel class. This section describes the method by which the URN TF is developed and evaluated. This effort has been presented at the International Conference on Underwater Acoustics (ICUA) and published in the 2022 proceedings [1].

4.1 URN Transfer Function Development Methodology

There are three steps to developing an URN TF for a class of vessels.

Firstly, representative class members are acoustically ranged over a range of vessel operation and environmental conditions. Each vessel's recorded URN is correlated with on-board measurements of its structure-borne noise, machinery states, hull fouling, and weather. This assumes sufficient class insight to identify representative members. Otherwise, a larger set of class members are selected for ranging. Then, unique class features are identified. For small vessels, these features are proposed to be: (i) length overall (LOA), draft, and tonnage; (ii) propulsion system; (iii) auxiliary equipment; (iv) hull form and hydrodynamic features; (v) cavitation inception speed, the extent that cavitation dominates their URN, and (vi) operating speeds.

In the second step, a TF is computed to predict the vessel's URN based on on-board measurements. A neural network is proposed as such networks can learn complex, non-linear relationships in multi-variate systems. In this case, the on-board measurements are the input features while the URN is the output. A supervised learning approach is proposed using measurements collected from the first step. While training the neural network, correlations in input features are identified as correlated features do not provide additional information to the network and can obscure the learned relationships. After training, the learned URN TF predicts the vessel's near-real-time URN through a sensor suite which measures the conditions. To optimize the design of such a sensor suite, the features of the neural network are analyzed in the third step.

The final step analyzes the sensitivity of the predicted URN to the on-board measurements. The resulting list of sensitive features indicates whether the URN signature for the class of vessel is dominated by cavitation, structure-borne noise, or hull noise at particular speeds. In addition, for the purposes of this project, the sensitivity analysis allows us to define a minimum viable instrumentation package for URN prediction towards CBM by ensuring the most sensitive features are measured by the selected instruments.

4.2 URN Transfer Function Model Design

In general, Machine Learning (ML) develops a model that relates input features to one or more output variables. For an URN TF, input features can include vessel characteristics (e.g., dimensions, draft, machinery states, etc.), vessel and environment interactions (e.g., water temperature, extent of hull fouling, maneuvers, sea state, etc.) and operational conditions (e.g., speed, aspect into sea state, etc.). The output would be decidecade URN frequency-domain spectra that relate to the on-board measurements. This is a regression problem since the output is a vector of real-valued scalars. Since labelled examples of expected outputs for input feature vectors are available to train the model, supervised learning can be applied. Given sufficient training examples, the model correctly predicts the output for an input feature vector not used in training.

We have chosen to use a neural network (also called a multi-layered perceptron (MLP)) as they are effective when applied to problems with large numbers of input features with complex relationships to the output vector that are unknown. A neural network is a fully connected network where values from one layer are passed through weighted links to subsequent layers. Training an MLP is the process of identifying the weights for each link in the network [2]. A disadvantage of MLPs is their lack of transparency in the predicted output and thus an inability to express this in an analytic form. Implementation of the MLP was achieved with the scikit-learn MLP Regressor. Multiple MLP structures were evaluated. The best performance was achieved for an MLP with a single hidden layer of 200 nodes. The input layer had 184 nodes (the number of input features) and the output layer had 27 nodes (the number of bins in the URN decidecade spectrum between 100 Hz and 50 kHz).

4.3 URN Transfer Function Training Approach

To train an MLP, many examples (i.e., pairs of input and output data) must be provided. In this case, each example corresponds to a particular run. These must be collected from representative class members under different conditions (i.e., speeds/operating conditions, environmental conditions, hull cleanliness levels, etc.), while measuring those conditions accurately. Following the K-folds cross-validation technique, the examples (runs) are divided into *k* equal subsets (folds), with (*k* − *1*) folds used for training and the final fold for testing (verification). The training and testing cycle is repeated *k*-times, once for each fold being used as the test set. The accuracy of the predicted URN compared to the measured URN is averaged across frequency bins for each test set to develop a consistency measure for the MLP's performance. Parameters of the MLP model are adjusted until the performance of the URN TF either matches a predefined criteria or reaches an optimum. This approach is shown in Figure 4-1.

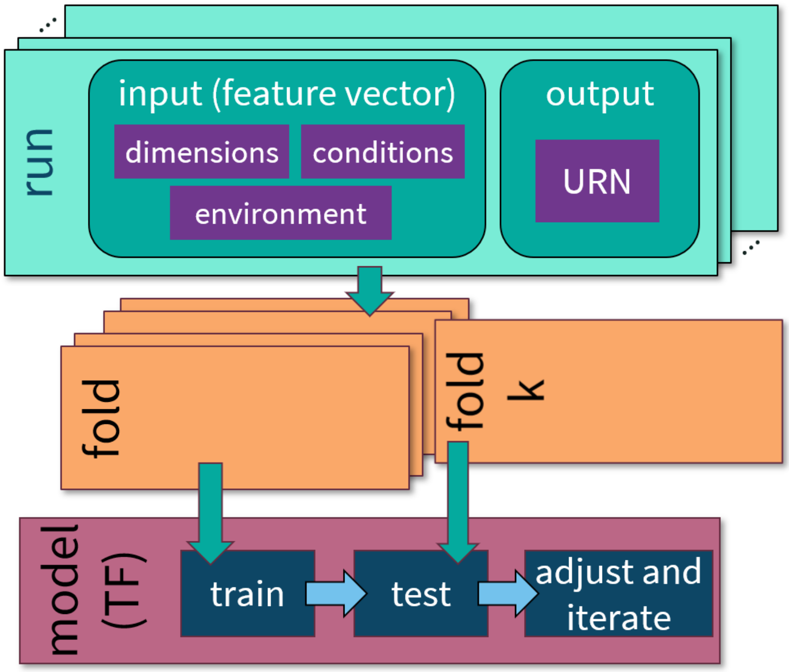

Figure 4-1 URN TF Training Approach

4.4 URN Transfer Function Performance

To evaluate the proposed URN TF methodology, preliminary testing was completing using the dataset collected under the previous TC project "Underwater Radiated Noise (URN) and Green House Gas Reduction Program for Canada's Inshore Fishing Craft" [3]. That document describes the acoustic ranging approach followed, the conditions, the specifics of the representative vessels from the Cape Islander class, and the dataset collected.

4.4.1 Cape Islander Dataset

In summary, five vessels were ranged three times resulting in 15 trials, each consisting of 4-6 runs each at different speeds. Input features measured for each run included: vessel characteristics (an arbitrary ID, age, and dimensions (beam, length over all, draft), engine size, number of blades on the propeller, engine strokes, whether the vessel was turbocharged, dry weight), date and weather conditions (time of day, wind speed, water temperature, air temperature, tide height, wave height), and operating conditions (planned speed, reported RPM, measured engine RPM, GPS-based speed over ground, number of passengers, fuel level, propeller cage presence, heading, measured power, fuel flow rate, whether the hull was cleaned before the trial, NSTM measure of hull cleanliness, what coatings were applied to the hull, the airborne noise level in the engine compartment, and the structure-borne vibration levels as measured on the engine mounts and on the hull above the propeller). The output was the decidecade URN spectrum between 100Hz and 50kHz for the run, averaged between the reciprocal passes in opposite directions. Measurement uncertainty is ~5 dB for the system.

4.4.2 Correlation Analysis

Excluding the airborne noise and structure borne noise spectra collected, a correlation analysis was run using all of the data collected for the Cape Islanders. The result is shown in Figure 4-2.

MLPs and other models perform best when there are few correlated features, as they cannot distinguish whether an output parameter is being driven wholly or in part due to one or each of a set of correlated input parameters. The five strongly correlated groups are listed below with retained features in bold:

- **NSTM level** and clean Boolean.
- planned speed, **speed over ground**, reported RPM, **RPM**, and **fuel flow rate**.
- **vessel dimensions (beam, draft, length overall, dry weight)**.
- **vessel dimensions**, fuel level, and **engine HP**.
- **water temperature** and **air temperature**.

This list shows that for the preliminary analysis, some strongly correlated parameters were retained as they were intuitively believed to be important to modelling a vessel's URN. Future work includes removing all but one variable from each strongly correlated group to better understand the MLP's sensitivity and performance with a very limited set of parameters.

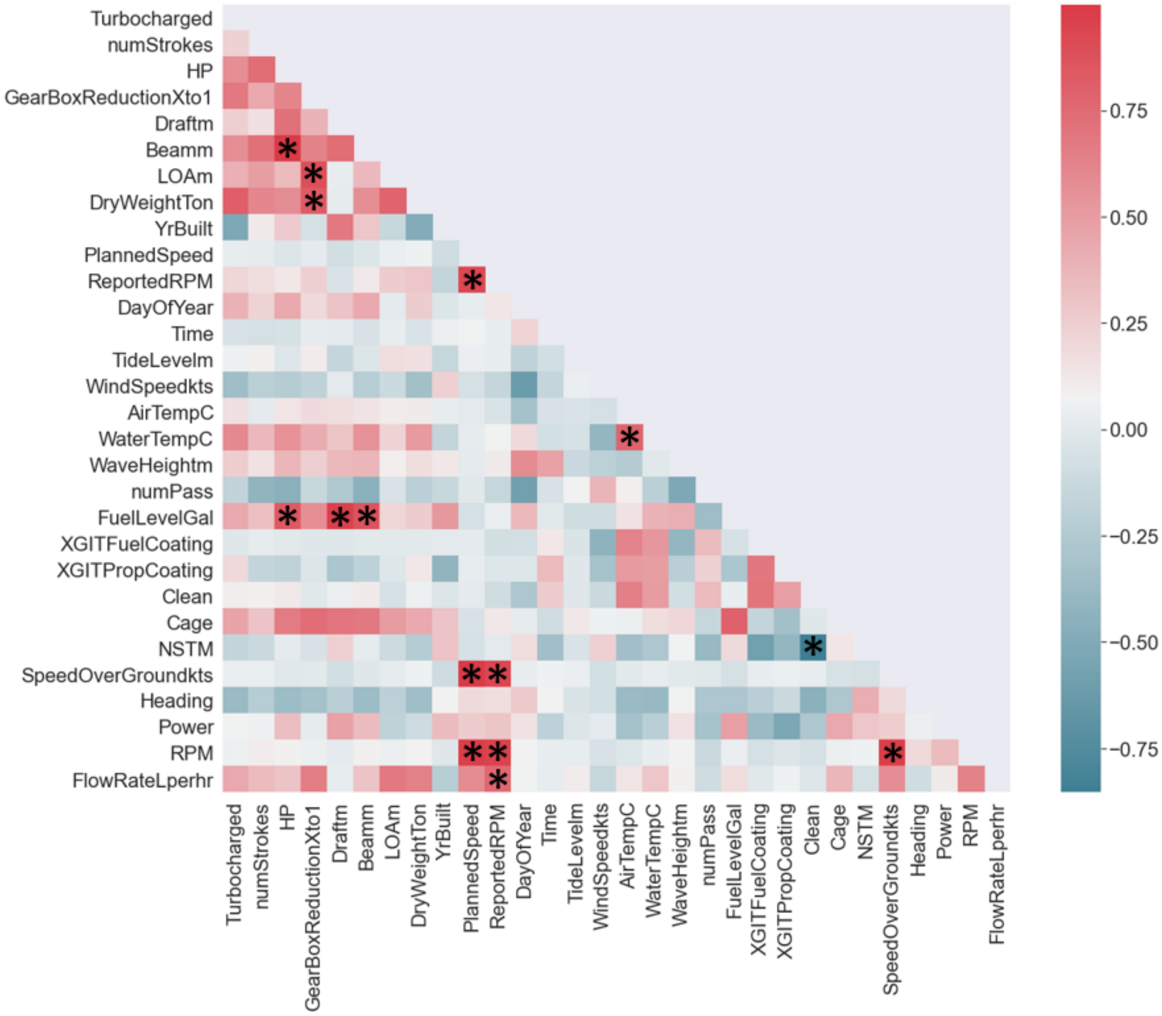

Figure 4-2 Correlation analysis results with intense blue or intense red indicating strongly correlated parameters. The strongest correlations are indicated by an asterisk (∗).

4.4.3 Results

The MLP training was performed using 5-fold cross-validation. The prediction errors for each fold and on average are summarized in Table 4-1.

Table 4-1 Prediction error of Cape Islander URN TF showing consistency among the folds. Good prediction accuracy and precision was achieved, given 5 dB measurement uncertainty.

fold	error [dB re 1 µPa at 1 m]	standard deviation [dB re 1 µPa at 1 m]
0	6.11	4.48
1	7.73	4.47
2	6.66	4.28
3	5.65	3.96
4	7.01	5.68
average	6.63	4.57

Each fold's prediction error, in each decidecade frequency bin is shown in Figure 4-3 with error bars showing one standard deviation from the mean prediction error for that fold's verification set.

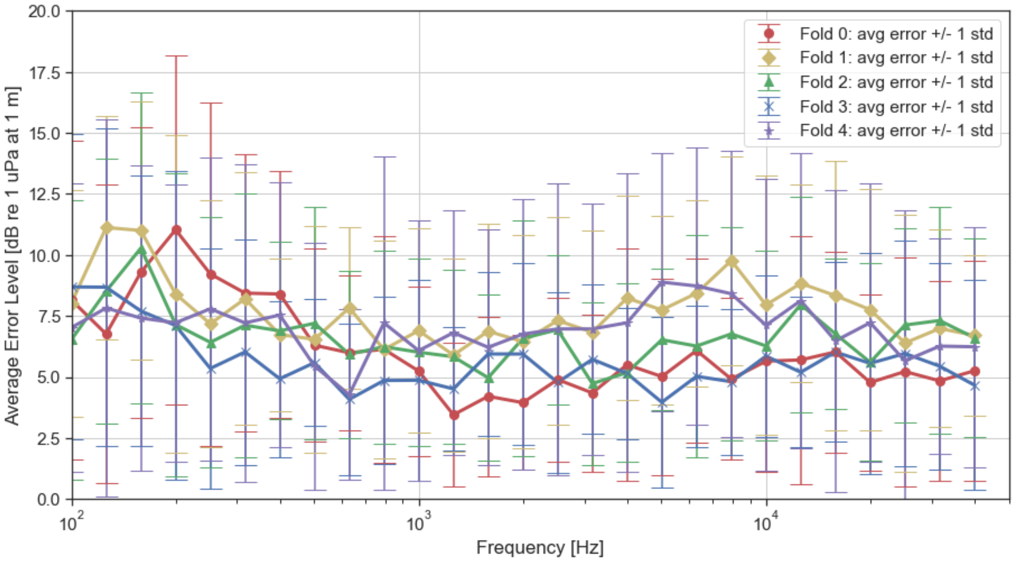

Figure 4-3 URN TF prediction error for each of the five folds, showing consistency across frequency bins.

The results across all five folds are consistent, meaning no particular run was poorer in accuracy than the others, nor that the URN TF was less effective for one of the vessels or conditions. On average, the URN prediction error was 6.63 ± 4.57 dB re 1 µPa at 1 m. This was generally higher at lower frequencies (below 400 Hz), which may be due to the higher low frequency ambient noise. The prediction error is surprisingly low given the measurement uncertainty was estimated at 5 dB, and minimal control of ambient noise levels were applied. This shows confidence in the efficacy of the proposed TF methodology.

4.4.4 Sensitivity Analysis

The ten most important features based on permutation importance analysis were: (1) Day of Year, (2) RPM, (3) Engine HP, (4) PropVib 10 Hz, (5) PropVib 12.59 Hz, (6) PropVib 15.85 Hz, (7) Power, (8) NSTM, (9) PropVib 19.95 Hz, and (10) PropVib 7.94 Hz. In this list, PropVib refers to a frequency bin for the accelerometer on the hull above the propeller.

This shows the expected trend that the model was sensitive to cavitation, vessel dimensions, the drive train, and vessel cleanliness. A notable Cape Islander class feature is that their URN is cavitation dominated. This is in the high permutation importance scores for several low frequency bins of the accelerometer located above the propeller. In the correlation analysis the engine power was highly correlated with the LoA for the Cape Islanders (bigger engines on bigger vessels). As well, the engine power's place in both analyses show the URN prediction generally depends on the vessel dimensions. Similarly, the impact of speed on URN prediction is shown by the presence of power, engine speed and fuel flow rate in these analyses which are correlated for diesel engines. The presence of NSTM in the permutation importance analysis reveals that hull fouling impacts the URN.

The sensitivity to the 'day of year' was unexpected. On reflection, 'day of year' represents environmental variables that impact underwater noise propagation like sound velocity profile, water temperature, salinity, underwater ambient, and sea bottom growth. Further, Cape Islander fishing operations are seasonal with annually varying installed equipment and maintenance (cleaning) activities. These seasonal operations were not otherwise captured and may have increased the sensitivity to the date. Future study is needed to understand the underlying factors that result in this 'day of year' sensitivity.

4.5 Day of Year Sensitivity

Although, the correlation analysis (see Figure 4-2) showed weak correlations between the 'DayOfYear' feature and several of the weather related features (wind speed, air temperature, water temperature) the performance of the URN predictor degraded when those features were used in place of the day of year indicating that those measures alone are not sufficient to capture the date-driven variance that influenced the URN. It is unclear whether the sensitivity to the date indicated the neural network was learning each day individually, or if there were underlying features during particular periods of the year that we could capture (e.g., changing equipment, underwater ambient noise levels, etc.).

The performance of the URN predictor was tested using a brute-force approach, where the 'DayOfYear' feature was incrementally replaced with weekly, monthly, and seasonal approximations (e.g., for the monthly approximation, all days in January were labelled as 0, February were 30, June were 150, etc.). It was found that dividing the year into three bins that corresponded to: before July (labelled 100), between July and mid-October (labelled 200), and after mid-October (labelled 300) resulted in the best performance. The performance using the 'DayOfYear' was on average 6.6 ± 4.6 dB, while with this approximation for 'DayOfYear' the performance was 6.7 ± 4.8 dB. This indicates that there is a seasonal variation driving the sensitivity to the date.

Whether this seasonal variation is driven by vessel conditions or environmental conditions remains unclear. However, if we look at the underwater ambient noise levels measured on each trial day (some days only one ambient was recorded, while on others there were multiple ambients recorded) there is a similar pattern. Figure 4-4 shows the recorded ambient levels, coloured to reflect the same divisions as identified for the date sensitivity (i.e., before July, between July and October, and after mid-October).

This suggests that the day of year sensitivity may be related to the underwater ambient level on the trial day. However, the segmentation of the ambient records by date is not distinct; there are many bins where they cannot be separated into three distinct seasons. While this is one step closer, future trials should be designed to either capture the underlying factors that may affect the day-to-day variation in URN levels or reduce the variance of those factors so that the URN TF can be developed without the impact of these unknown variables.

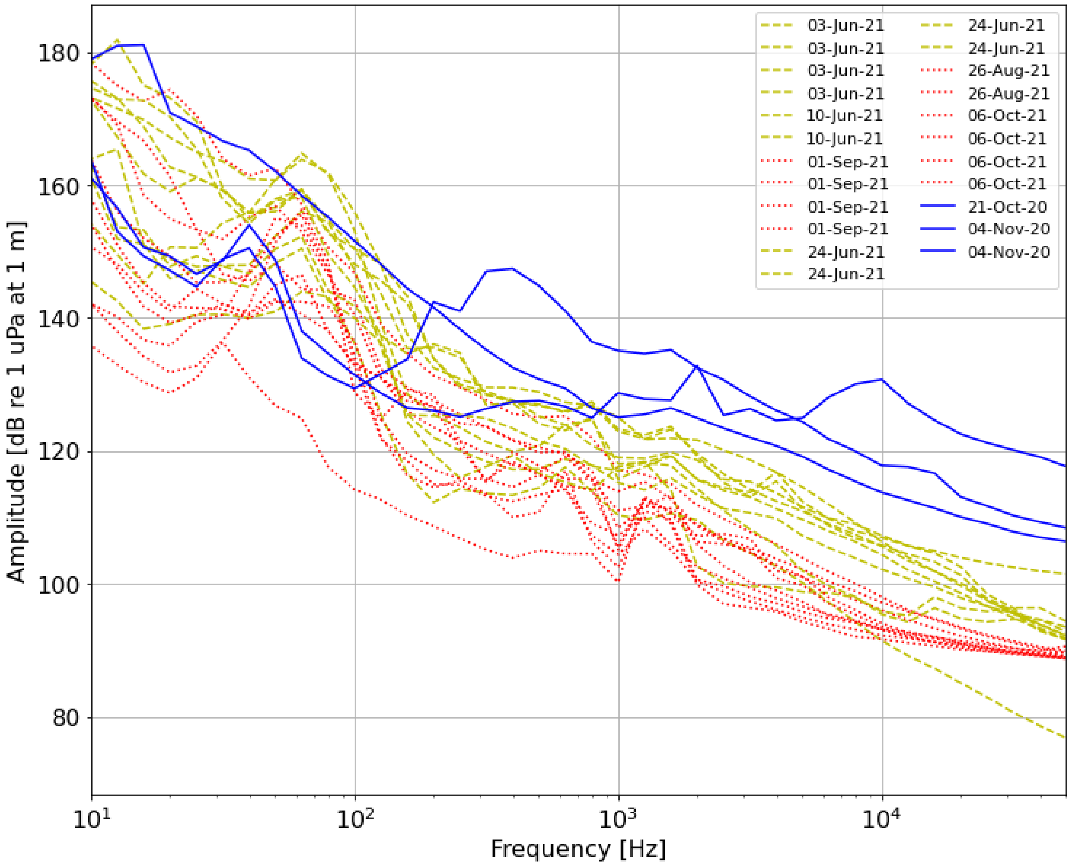

Figure 4-4 Underwater ambient noise levels during Cape Islander Trials between 2020 and 2021. Colours indicate records taken before July (pink), between August and early October (cyan), and after mid-October (blue).

4.6 URN Transfer Function Feature Set Recommendations

The URN TF sensitivity analysis provided insight into how the predicted URN varied due to individual parameters. For the development of an instrumentation package for CBM it is of interest to know how the performance changes with a particular set of features. With this in mind, a set of features were chosen that would be easy to collect using a minimally invasive instrumentation package, based on this performance the features were adjusted until the complexity of the features was balanced with the overall performance of the URN TF.

4.6.1 Analysis towards a Reduced Feature Set

Based on their high sensitivities in the previous analysis, the feature set began by keeping the seasonal approximation for 'Day of Year', 'Engine RPM', and the full spectrum from the accelerometer placed on the hull above the propeller (called 'PropVib' for short).

The sensitivity to the 'YrBuilt' feature (i.e., the year the vessel was constructed which ranged from 1979 through 2015) was of concern as its value was unique to each of the vessels tested. To ensure the neural network was not learning to estimate the URN for each individual vessel, the Year Built was reduced to the Decade Built (i.e., if built before 1985 the vessel was labelled as 1980, if built before 1995 the vessel was labelled as 1990, if built before 2005 the vessel was labelled as 2000, and if built before (or in) 2015 the vessel was labelled as 2010). This resulted in no change in performance accuracy.

Noting the high sensitivity to the vessel dimensions, each dimension (breadth, draft, LOA, dry weight, and engine HP) was tested to determine which had the best performance. The results were quite similar, with slightly better performance when engine HP was included in the feature set.

Finally, the extents of the frequency range for the 'PropVib' feature were reviewed in two ways. To begin, the spectrum was divided into subsets where each subset contained one decade of decidecade bins (i.e., < 10 Hz; 10 to 100 Hz; 100 Hz to 1000 Hz; 1000-10000 Hz; and > 10000 Hz). Each subset and combinations of these subsets was tested. This showed that the URN prediction accuracy was maintained when trained included the 10-100 Hz frequency range at minimum. Next the decidecade bins within each of the subsets were averaged in different ways. We considered a) one bin comprising all recorded decidecade bins, and b) one bin comprising all recorded decidecade bins between 10 and 100 Hz. Both a) and b) were found to have no negative impact on the performance of the URN prediction. This suggests that it would be acceptable to use an accelerometer that measures the vibration per decade between 10 and 100 Hz, rather than the vibration in each decideacde bin.

The resulting set of features were: Season of Year, Decade Built, Engine HP, Engine RPM, and 'PropVib' for the decade between 10 and 100 Hz. Note that each of these features are only a single value (none are arrays / vectors). This set resulted in minimal performance degradation at 6.6 ± 4.6 dB re 1 µPa at 1 m, demonstrating that many of the recorded features were strongly correlated and providing no additional information to the URN TF. These five features are considered to be the minimal viable feature set for a Cape Islander class URN TF.

Since this analysis is based on a preliminary dataset which showed high sensitivity to the 'Day of Year', several additional measures were included in the trials conducted during the Fall of 2023, as described in the recommendations below.

4.6.2 Recommendations

Based on this analysis, the CBM instrumentation package (including both vessel operator-provided data as well as sensor data) should collect the following information at minimum:

- Engine RPM.
- Structure-borne vibration of the hull above the propeller (priority on ~10-100 Hz decade band).
- Engine horsepower (HP) (static vessel characteristic).
- Day of the Year (to be converted into a season, based on the ambient recorded).
- Year the vessel was built (to be converted into a decade).

In recognition that the analysis is based on a preliminary dataset collected for a slightly different purpose and spanning more than a year, it would be beneficial to gather some additional features. These features include those that are typically needed to generate analytical or numerical models for a vessel's URN and can be used to review and hopefully confirm the correlations and insights from the preliminary dataset. If possible, the instrumentation package should also collect:

- Structure-borne vibration at the engine mount.
- Weather: air temperature, tide level, wind speed, wave height.
- Hull cleanliness/fouling extent (NSTM level).

As mentioned in the discussion of the sensitivity to the day of the year sensitivity, it would be beneficial to collect future datasets over a shorter period of time (e.g., a few weeks) to reduce the trial-to-trial variation in equipment presence, vessel/engine/propeller maintenance, and environmental conditions (e.g., weather, state of the seabed). Simultaneously, additional measures of variation between trials should be tracked to explain any such sensitivity. These additional measures should be developed in coordination with the Cape Islander operators/owners who have the best insight to why their vessels may perform differently day-to-day.

5. Instrumentation Package

The instrumentation package is composed of two parts, Data Processing, and Data Acquisition; the latter being further subdivided into Analog-Digital Conversion (ADC) and Sensors.

Data processing is handled by a computer, where measurements obtained from the Data Acquisition side are used in calculations which yield useful numerical results. In the case of this project, vessel Vibration, Speed, and Engine RPM measurements are used as inputs to a transfer function trained to predict URN. This section considers various options for building a low-cost instrumentation package.

5.1 Data Acquisition

Upon research of the options available for long term, in situ Data Acquisition, Analog Digital Conversion is of critical consideration – it must be decided what kind of analog signal is to be produced by the sensors and acquired by the ADC.

For the purposes of this project, the type of accelerometer used determines the ADC requirement for Data Acquisition. Consequentially, other analog sensors should conform to the type of signal produced by the accelerometers to prevent unnecessary redundancy in ADC components.

5.1.1 Accelerometer(s)

The two types of accelerometers considered for this package are Integrated Electronics Piezo-Electric (IEPE) accelerometers which produce a dynamic signal transmitted as a voltage representing the vibration measured, and 4-20 mA accelerometers which transmit a current which corresponds to either the RMS or Peak vibration trend.

IEPE accelerometers produce a dynamic voltage signal that corresponds to the acceleration experienced at the point of measurement. This signal can be used to perform frequency analysis of the vibration at the point of measurement through FFT and can be computed into RMS or Peak trend data. IEPE sensors require constant current power supplies and ADCs which conform to the specification. IEPE data acquisition systems cost significantly more than 4-20 mA systems.

The 4-20 mA accelerometers produce a current that corresponds to either an RMS or Peak vibration trend at the point measured within a predefined frequency range. 4-20 mA sensors are commonly used in industrial settings for continuous monitoring applications, and readily interface with PLC systems. Thus, data acquisition systems for these sensors are less costly than IEPE systems. 4-20 mA accelerometers are more limited in the frequency range they can measure, and frequency analysis cannot be performed with data obtained from 4-20 mA accelerometers, as they only output an overall RMS or Peak level within the frequency band specified and not a dynamic signal representing the vibration at the measurement point.

4-20 mA accelerometers are tuned to a maximum vibration level they can measure, with the “full-scale” amplitude being read at an output current of 20 mA. Vibration levels exceeding this maximum will remain as an output of 20 mA, so care must be taken to select an accelerometer with an appropriate full-scale vibration level. Velocity RMS levels above the propeller of Cape Islander fishing boats in a previous study were found to generally not exceed 50 mm/s between 2.5-Hz-20kHz. However, some data points taken at very high and atypical engine RPMs put the maximum measured velocity RMS at 75 mm/s between 2.5-Hz-20kHz [3].

5.1.2 Vessel Speed

Vessel Speed Over Ground (SOG) is easily acquired via GPS. Many GPS devices exist which interface to computers via serial cable, USB, and Ethernet.

Vessel Speed Through Water (STW) is the vector between the vessel's Speed Over Ground and the Water Resistance experienced by the vessel. Water current speed is generally measured via a paddlewheel transducer. Collecting this information is likely not necessary, as large current effects can be inferred from relatively high engine RPM corresponding to slower SOG, and engine RPM alone is enough to predict URN.

5.1.3 Engine RPM

Engine RPM is determined either via direct measurement of the physical rotation produced by the engine with optical, proximity, or magnetic sensors or inferring it by measuring electrical pulses of equipment related to engine combustion processes, such as spark plugs for a gas fired engine, fuel injectors of diesel engines, or pulses produced by rotation of an alternator. Devices can output RPM measurements as a voltage pulse or 4-20 mA current – both kinds of device are commonplace and are not significantly different in cost or accuracy.

Hall-effect sensors are commonly used to measure engine RPM, are inexpensive, and are built for industrial environments. They work through measuring the presence of a magnetic field, usually though a magnet attached to a piece of rotating machinery, or from a magnet housed inside the sensor interacting with a ferrous material such as gear teeth.

5.2 Data Processing

Data acquired is used as inputs for the URN transfer function. The computer used for data processing must be capable of performing the necessary calculations. Single Board Computers (SBCs) are small form factor but are fully featured computers capable of complex calculations, data processing, and display.

5.2.1 Single Board Computer

Many SBC options exist, with the most prominent and widely used being the Raspberry Pi. Processor architecture of the SBC is of significant consideration, as the manufacturer of DAQs most used with IEPE accelerometers, National Instruments (NI), does not offer driver support for ARM processor architectures, limiting SBC selection to x86/x64 architectures only if NI DAQ equipment is used. The Raspberry Pi has an ARM processor and would be incapable of interfacing with NI DAQ equipment.

Specific attention is brought to NI equipment as LR already owns an NI IEPE accelerometer DAQ system that could be used to validate any system built, so reference to an instrumentation package that is directly comparable to this equipment is included.

It was determined that frequency analysis is not essential to the URN transfer function, so IEPE DAQs, and thus NI equipment, are not necessary, and the Raspberry Pi SBC is more than sufficient. Nonetheless, an IEPE Raspberry Pi based system is included as an example of a mid tier system capable of performing frequency analysis.

5.2.2 Vessel Data Input

The URN transfer function requires specific vessel characteristics as input parameters, such as draft, propeller characteristics, engine horsepower, and date of build. Other information could be collected for correlative purposes, such as when maintenance occurs and what maintenance was performed. Vessel characteristics and other correlative information can be user defined in SBC software accessible to the end user of the instrumentation package.

The SBC URN prediction software requires a user accessible Graphical User Interface (GUI) capable of displaying sensor measurements, taking inputs of vessel parameters used by the transfer function, and the resultant URN prediction. Vessel characteristic parameters would be defined during setup of an instrumentation package on a vessel through the GUI but could be altered later if necessary.

The URN prediction software at its most basic would take sensor measurements, calculate the URN transfer function, and display the result. However, it would be possible for the SBC software to log sensor measurements and resultant URN predictions, display historical data and URN trends, and perform statistical analysis of measurement data.

Correlations between historical datum could potentially be used for condition-based monitoring, notifying the user when relationships between measurements deviate significantly from historical norms. For example, higher than average RPM measurements coupled with lower-than-average speed measurements could indicate engine performance issues. Or increased propeller vibration and engine RPM measurements at lower vessel speeds could indicate hull and propeller fouling.

5.3 Instrumentation Package Options

The minimally viable instrumentation package would consist of an accelerometer positioned above the propeller capable of outputting RMS velocity between 10-100 Hz with a maximum reading of at least 100 mm/s, an engine RPM sensor, and an SBC and DAQ capable of taking measurements from these sensors, processing them, and displaying the predicted URN. This system would enable URN to be predicted and displayed in real-time, informing the decision-making processes of vessel operators looking to reduce their environmental impact.

Capabilities in addition to this base package, such as data logging and additional sensors, would enable condition-based monitoring through the analysis of historical trends and correlations between sensors. A second accelerometer attached to the engine could be used to establish possible engine issues based on historical trends. GPS and weather sensors can all be added to the package with little additional difficulty.

Example instrumentation packages are outlined in the following two tables. A complete instrumentation package will be composed of one option from each table, i.e. A-1, C-3, etc.

Table 5-1 SBC and Accelerometer Options

Component	A	B	C
SBC	LattePanda 3 Delta 864 ($279)	Raspberry Pi 4 Model B 4GB ($76.95)	Raspberry Pi 4 Model B 4GB ($76.95)
Accelerometer	IEPE	IEPE	4-20 mA
DAQ	NI-9250 Vibration Input Module ($2,615) + cDAQ-9171 ($740)	MCC 172 IEPE Measurement DAQ HAT for Raspberry Pi ($502.46)	Pi-SPi-8AI Raspberry Pi Analog Input (4 - 20 mA) Interface ($37.71)
Cable	BNC	BNC	4-20 mA Current Loop
Power supply	12V DC ($5)	5.1V DC ($9.95)	5.1V DC ($9.95)
Bonus features	Frequency analysis, 2 Accelerometers	Frequency Analysis, 2 Accelerometers	Up to 8 accelerometers
Total	>$3,639	>$589.36	>$124.61

Table 5-2 RPM and Additional Sensor Options

Option	RPM Sensor	GPS	Weather	Total
1	Honeywell 103SR13A-1 Hall-effect Sensor ($62.50) + Magnet	-	-	$109.10
2	Honeywell 103SR13A-1 Hall-effect Sensor ($62.50) + Magnet	GNSS200L Industrial high sensitivity USB GNSS Receiver ($69.95)	-	$179.05
3	Honeywell 103SR13A-1 Hall-effect Sensor ($62.50) + Magnet	GNSS200L Industrial high sensitivity USB GNSS Receiver ($69.95)	ECOWITT Wittboy Weather Station ($269.99)	$449.04

We chose to build a C-1 for this project as GPS is not used by the transfer function and is unnecessary to include in the build. The C-2 would be considered as the CBM instrumentation package for general use where logs of speed and location were of interest. C-3 would also be of interest, however given the significant relative cost increase of the weather station and the limited additional value of the data it provides, it is not preferred.

5.4 Prototype CBM System

A C-1 system was ultimately built for this project. A Raspberry Pi Model 4B 8GB SBC, Pi-SPi-8AI+ DAQ, Honeywell 103SR13A-1 Hall-effect Sensor, and Wilcoxon PC420-VR-50 4-20 mA Accelerometer were procured along with required cabling and casing as seen below.

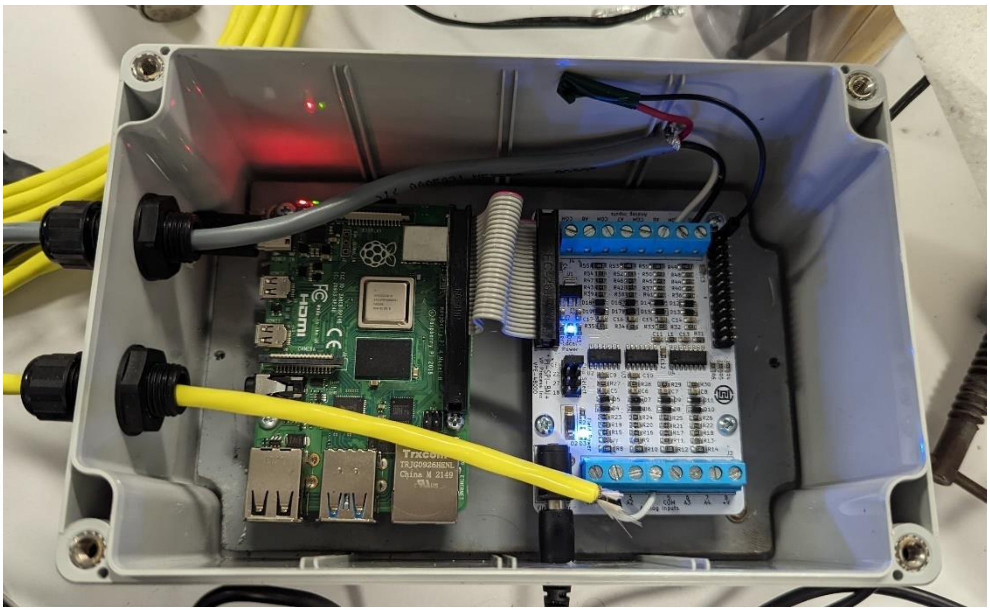

Figure 5-1 CBM C-1 Prototype Internals. Left: Raspberry Pi 4B. Right: Pi-SPi-8AI+ Raspberry Pi Analog Input (4 - 20 mA) Interface.

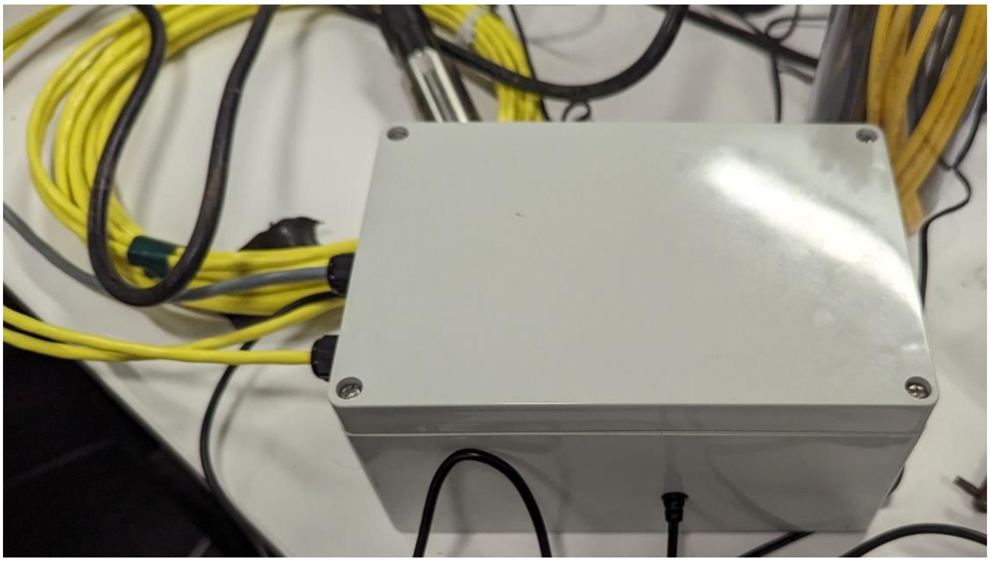

Figure 5-2 Assembled CBM C-1 Prototype

Figure 5-1 shows, from left to right, the Raspberry Pi 4B SBC and Pi-SPi-8AI+ DAQ insert into a weather resistant case with holes drilled for the tachometer, accelerometer, and power cables. Figure 5-2 shows the case screwed shut. The yellow cable is attached to the Wilcoxon 4-20 mA accelerometer and the grey cable is attached to the Honeywell Hall Effect sensor used as a tachometer.

The Pi-SPi-8AI+ DAQ has eight analog inputs. Four inputs read 4-20 mA current sensor outputs, and the remaining four inputs read 0-6.6 VDC voltage sensor outputs.

Figure 5-3 CBM system in-situ on a fishing boat trial powered from a portable power pack.

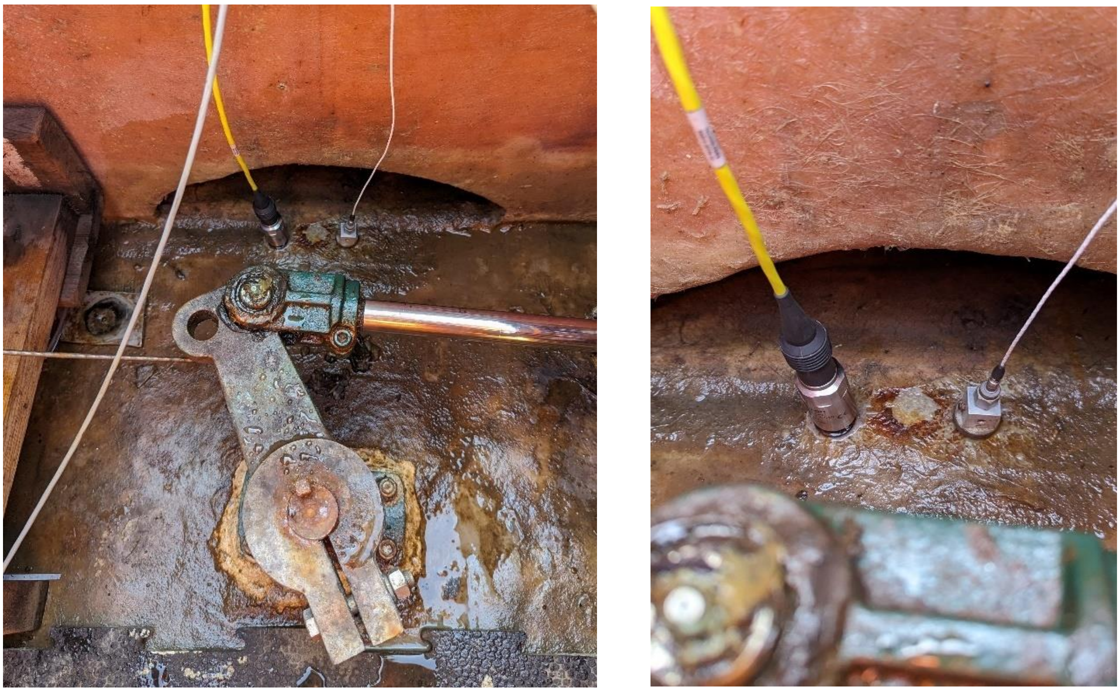

Figure 5-4 Two accelerometers mounted on hull above fishing boat propeller. Mounted Left: CBM 4-20 mA Wilcoxon Accelerometer. Mounted Right: IEPE reference accelerometer.

Figure 5-5 Hall Effect Tachometer mounted to hull pointed towards propeller shaft with tachometer triggering magnet taped to shaft.

Figure 5-6 Close up of Hall Effect Tachometer and triggering magnet.

5.4.1 Prototype CBM System Software

The Raspberry Pi SBC performs all data logging, data processing, GUI web serving and Wi-Fi access point networking functionalities. The data logging and processing software of the CBM system was written in Python. The WebApp GUI was written in JavaScript using the ReactJS library and is hosted locally on the Raspberry Pi using a Python based webserver. The Web App is accessed by connecting a suitable device to the Wi-Fi access point generated by the Raspberry Pi and visiting the domain raspberrypi.home:3000 in a JavaScript enabled web browser.

Sensor outputs are digitized by the Pi-SPi-8AI+ interface and are continuously read, timestamped, and logged to a database by a Python script running on the Raspberry Pi. There is a data processing script running in parallel to the data reading and logging script which accumulates buffers of 1000 sensor data points at a time. This buffer contains the last 1000 outputs read from the tachometer and accelerometer. The buffer points are used to determine average propeller shaft RPM and velocity RMS of the hull above the propeller over the buffer duration, which are then input to the URN prediction transfer function along with boat specific variables. The spectrum output by the transfer function, along will all transfer function inputs - including the determined shaft RPM and velocity RMS - are also timestamped and logged to the database in a separate table.

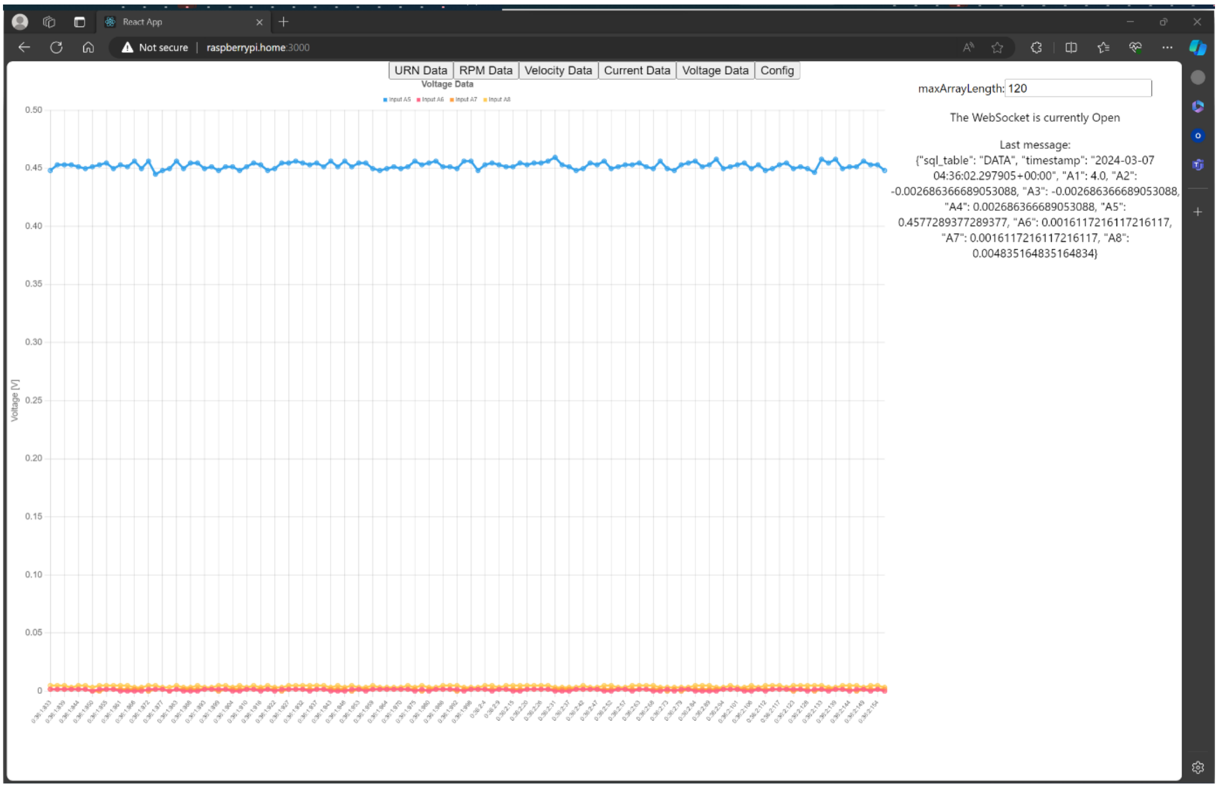

Figure 5-7 Screenshot GUI webapp accessed via a smartphone web browser plotting a real-time stream of voltage data read from the Pi-SPi-8AI+. Input A5 is the output read from the hall effect tachometer.

The voltage data buffer read from the tachometer is used to determine the average shaft RPM over the buffer duration by measuring the duration between voltage dips caused by the magnetic triggering of the hall sensor via a peak finding algorithm.

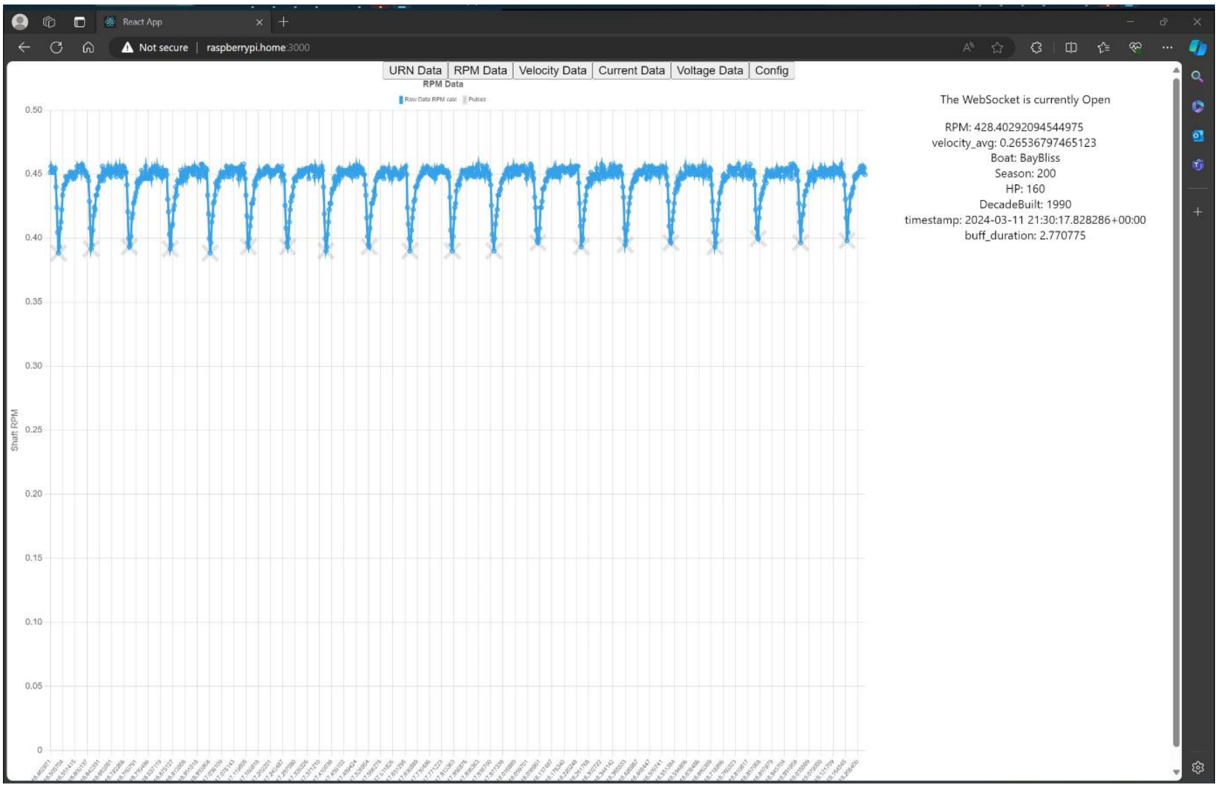

Figure 5-8 Webapp GUI displaying a plot of the 1000-point data buffer of tachometer voltage data along with the peaks found via the peak finding algorithm used to determine average shaft RPM over the duration of the data buffer. Timestamps are logged in UTC and were displayed as such in this plot.

The Wilcoxon accelerometer outputs a current between 4-20 mA which maps to an RMS velocity of 0-127 mm/s. This current is read by the Pi-SPi-8AI+ and is written to a database without conversion to velocity RMS. The current is averaged and converted to mm/s RMS in the data processing buffer and logged in the processed data table.

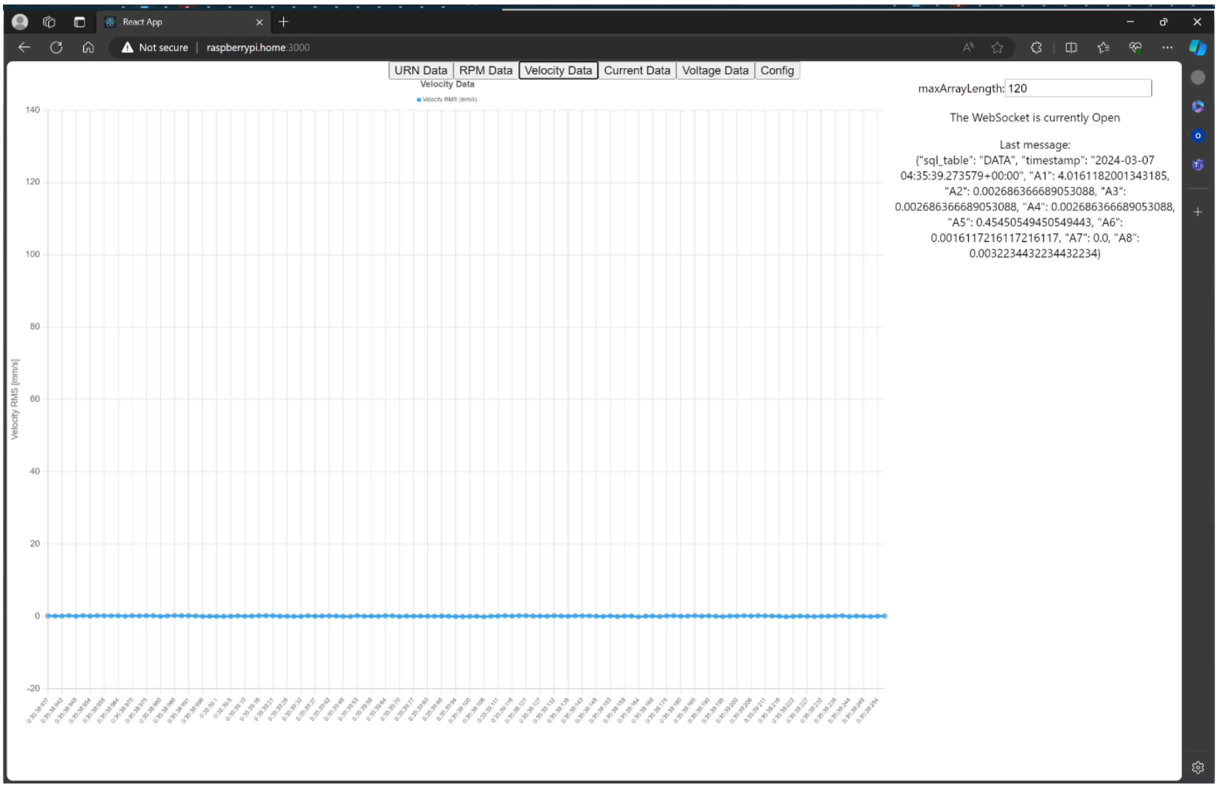

Figure 5-9 Webapp GUI plotting real-time stream of velocity RMS data measured from the 4-20 mA Wilcoxon accelerometer.

The URN transfer function also requires boat specific parameter inputs, such as boat engine horsepower and date of build. The parameters used by the data processing script for the transfer function can be set in the Webapp GUI as seen in Figure 5-10.

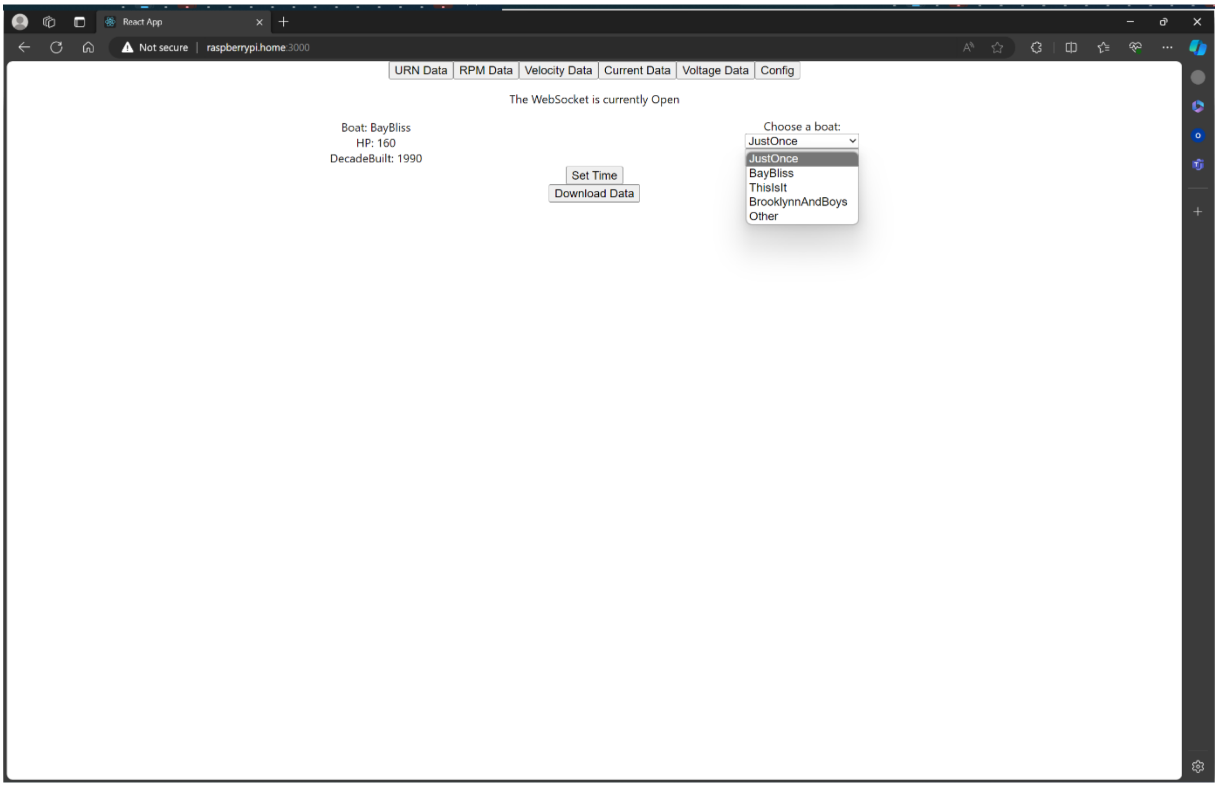

Figure 5-10 Boat parameter input interface in the webapp GUI.

The dropdown menu contains boat parameter presets for all boats involved in this trial, as well as an option to add custom boat data if the need arises. The “Set Time” button syncs the Raspberry Pi system clock to the clock of the device accessing the webapp. This button was included to ensure accurate datalogging timestamps while lacking a real-time clock (RTC) module on the Raspberry Pi. Without an RTC, the Raspberry Pi will not keep time between power cycles and normally relies on internet connectivity to sync its clock. Since the CBM system does not connect to the internet, an external clock source such as one provided by a smartphone or laptop is necessary. This issue can be avoided with the addition of an inexpensive RTC module for the Raspberry Pi.

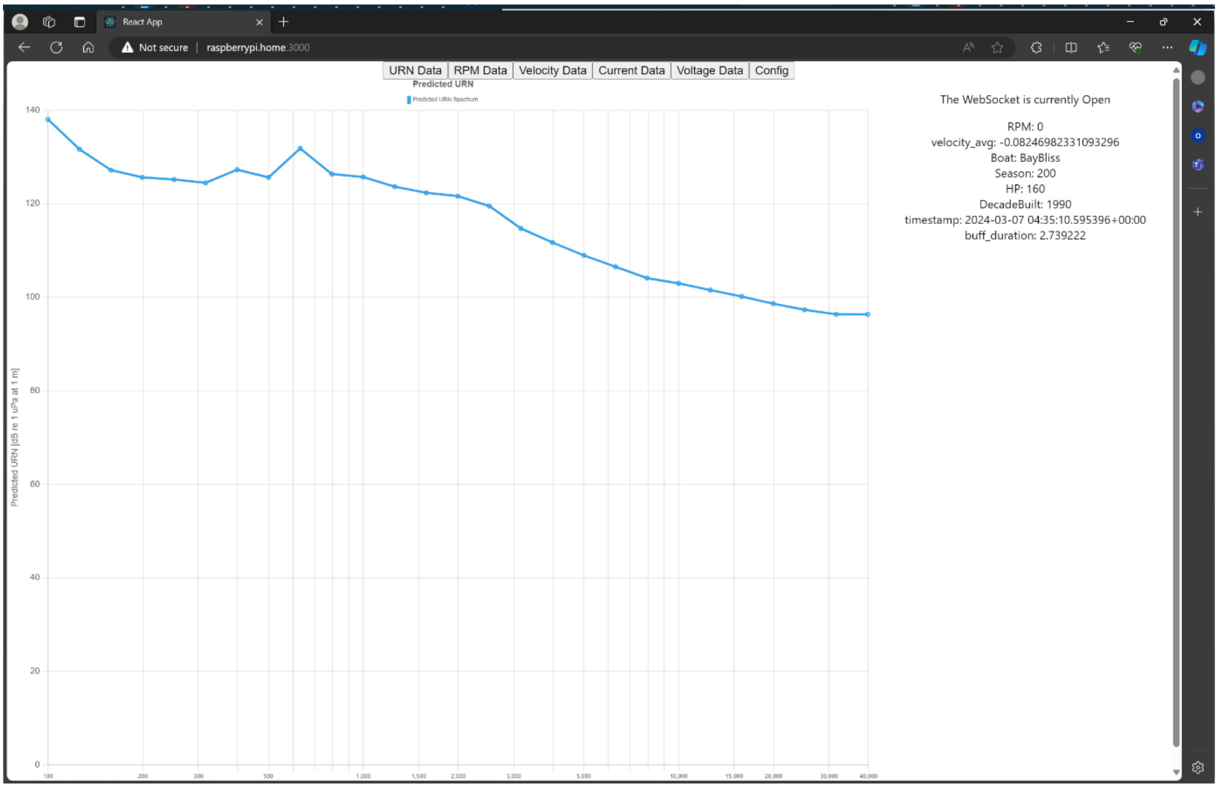

Figure 5-11 Predicted URN spectra plot by the webapp GUI as determined by processed tachometer and accelerometer inputs and boat specific parameters.

Figure 5-11 shows the spectra output by the URN transfer function as well as all parameters input to produce it in the text to the right.

5.5 Trials with Prototype CBM System

Sea trials, as described in Section 3 Trial Method and Data Collection, were undertaken with fishing boats equipped with the prototype CBM system which travelled past hydrophones measuring the URN produced by each boat at varying speeds during dynamic trials, and varying engine RPM during static trials.

Figure 5-12 Photo of the support vessel with hydrophone system deployed as the boat under test passes during a sea trial.

Sea trials with the CBM system on the four fishing vessels went smoothly after getting used to the specifics of setting up the sensor hardware. Alignment of the tachometer toward a trigger with a sufficiently strong magnetic field is essential. Early trials suffered minor delays with system installation due to magnet placement and fixturing to the shaft. A weak magnet was replaced with a spare that performed better, and unnecessarily thick tape that impeded the magnetic field was removed and replaced with thinner electrical tape which did not impede the field. After best practices for the hall effect tachometer were found, installation of the system was fast and efficient.

There were no significant issues experienced with the CBM system itself during trials. It reliably read, processed, and logged data as expected, and system parameters were configured via the WebApp GUI as expected and without issue. The few issues that were encountered were related to the sensor mounting; in one case the magnetic base accelerometer was dislodged from the steel plate attached to the hull, and in another the Hall-effect sensor mount became loose and the sensor moved away from the triggering magnet resulting a loss of RPM data. However, there were no failures of sensors or data acquisition hardware and the mounting issues could be resolved by using more permanent mounting fixtures rather than the temporary mounts used during the trials.

Monitoring sensor outputs and processed data via the WebApp GUI ensured sensors were installed properly and working as expected. The WebApp GUI was primarily used by smartphones throughout the trials and was fast and convenient to use. A tablet was also used to access the WebApp GUI once during a trial.

Fishing boat captains were shown the WebApp GUI and had interest in the data displayed. They were curious to know the findings of our study and if a URN predicting CBM system such as the one field tested could improve their fishing or help reduce their impact on the environment. Future considerations for the WebApp GUI could incorporate limits related to marine life of interest and more obvious indicators of when those limits are exceeded.

6. URN Transfer Function Results

6.1 Results Using 2020/2021 Data for Training

It was intended to use the 2020/2021 fishing vessel URN measurements [3] to train an MLP, as described in Section 4, and use the URN data collected during the current project (trials conducted September-October 2023) to verify the system performance. However, the ambient levels recorded in 2020/2021 differ from those record in 2023. In the band between 100-1000 Hz, the 2020/2021 records show levels between approximately 110-130 dB while the 2023 records are between approximately 90 – 120 dB, as shown in Figure 6-1. This difference in recorded level is also reflected in the recorded URN from the vessels that participated in both trials, as given in Figure 6-2.

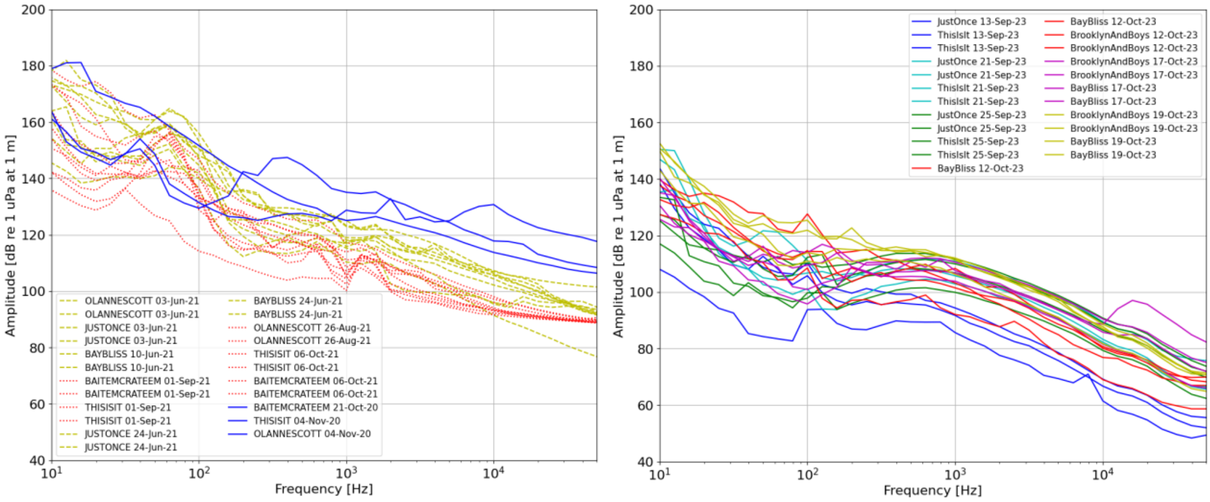

Figure 6-1 All ambient recordings in 2020/2021 (left) and 2023 (right).

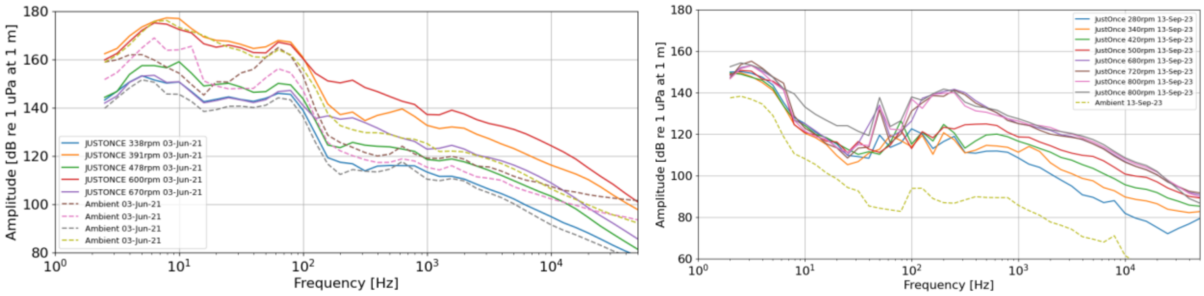

Figure 6-2 Just Once (clean no cage, not freshly coated) from 2020/2021 (left) and 2023 (right).

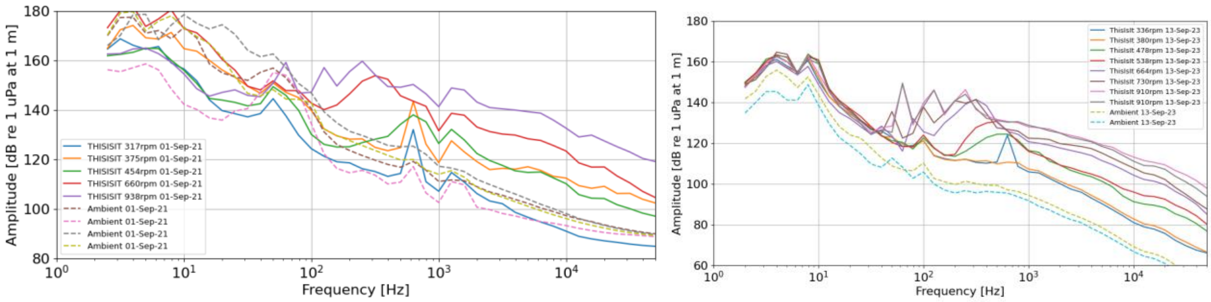

Figure 6-3 This Is It (clean no cage, not freshly coated) from 2020/2021 (left) and 2023 (right).

The reason for these differences in the measured results have not been confirmed. There are several factors that could influence the measurements:

- The 2020/2021 trials were conducted in an estuary in shallow water (20m), whereas the 2023 trials were conducted in open water that was relatively deep (50m) water.

- The 2020/2021 measurements were obtained with a single hydrophone located near the surface. The 2023 trials used two hydrophones located at 15m and 40m depth.

Given this difference, the URN levels predicted by the CBM using the URN TF trained on 2020/2021 records were inaccurate.

6.2 Results Using 2023 Data for Training

To overcome the discrepancies in the URN data sets, a new URN TF was trained and tested on 2023 data alone, using both the trials without the cages and with the cages (the fouled cage trial data was not included in the training and testing dataset).

The process for training and testing the MLB with the 2023 trial data is very similar to that applied to the 2020/2021 dataset, as described in Section 4, with two exceptions:

- First, the 2020/2021 URN TF was trained on the URN spectra for each speed calculated from reciprocal runs as required by ISO 17208. Instead, the 2023 URN TF was trained using each individual run (i.e., not averaged direction for currents). This is because the URN TF is intended to provide an estimate of the URN for a vessel based on engine/shaft RPM, not speed over ground.

- Second, the 2020/2021 URN records were recorded using one hydrophone, while the 2023 recordings were made on two hydrophones (one at 15 m depth and the other at 40 m depth). As specified in the LR ShipRight ADP for URN, each recording is compared to the background noise (Ambient) level. If the URN signal at any frequency bin is < 3 dB above the background noise, that bin must be excluded, otherwise it is corrected using the correction in ISO 17208. The multi-layer perceptron multi-output regressor used to train the URN TF cannot learn when there are 'gaps' in a target URN spectrum. As a result, runs in which there are fewer than two frequency bins that should be excluded are used with those frequency bins included. Otherwise, that hydrophone record is considered invalid. If both hydrophone records are valid, they are averaged. If only one of the two hydrophone records is valid, it is used. If neither hydrophones' records are valid, that run is excluded from the train/test set.

As noted in CBM section, the Accelerometer became dislodged during one of the trials and there were some dropouts of the Tachometer. As a result, two additional runs were excluded from the training set. This results in 51 runs from the 2023 trials that could be used in the training/testing set.

As before, the records were divided into 5 folds for cross-validation (each fold contains a unique subset of records which includes some examples from each boat, speed, and cage/no cage state). Five training/testing iterations were performed where each iteration used one fold for testing and the other four for training. This provides insight into the consistency. If the test results from one of the folds is significantly better or worse than the other four for the same model hyperparameters, this would indicate one or more of the examples from that set are outliers that could skew the trained model. The prediction errors for each fold and on average are summarised in Table 6-1.

Table 6-1 Test performance of URN TF trained on 2023 records

Fold	Average error [dB]	Maximum error [dB]
0	3.7	17.5
1	4.7	24.0
2	6.1	17.1
3	4.9	16.1
4	6.3	117.1
Average	5.1	38.3

Each fold's prediction error, in each decidecade frequency bin, is shown in Figure 6-4 with error bars showing one standard deviation from the mean prediction error for that fold's verification set.

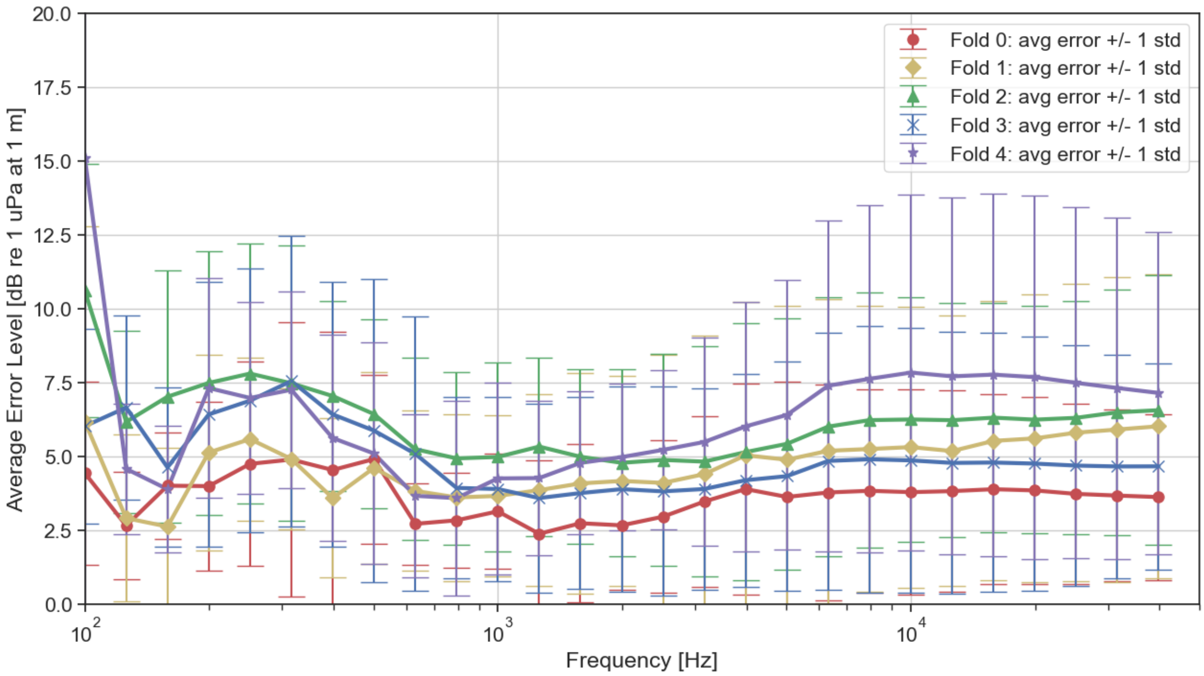

Figure 6-4 Average Error on Training Set by Frequency Bin

The average error of 5.1 dB is similar to the average error when training on the 2020/2021 records. This indicates that this type of data is well suited to this type of learning model. However, the inability to apply the model learned on 2020/2021 records to the 2023 trials indicates that measuring the same vessels in different locations may not result in consistent URN levels. This points to the importance of using measurement techniques that account for factors such as shallow water effects, bottom type, and bathymetric geometry when conducting URN measurements for a given class of vessels.

6.3 Alternate Training Approaches

Additional work was carried out to investigate the impact of separating the records other than by general randomization in folds. The first approach separated the records by whether the boat had the cage installed (training with "no cage" records and testing "cage" records, and vice versa). The second approach used records from three of the boats for training and testing with records from the fourth boat. While these models would not be deployed, they do indicate how well the model can generalize across sub-groups within the dataset.

When separating the data by the cage/no cage feature the results in Figure 6-5 were obtained. In this figure, each colour indicates a different record in the testing set with the solid line showing the logged URN and the dashed line showing the predicted URN using the learned TF. The following observations were made:

- When training on no-cage data and testing on data recorded with the cage, the error was larger (9.4 dB on average), and the predicted URN had a much wider 'spread' than the measured URN. This implies that the URN records without the cage are more variable among the boats than their URN levels with the cage installed.
- When training on data with the cage installed, and testing on records without the cage, the predicted URN levels are generally higher than the corresponding logged URN levels. This

suggests that the vessels are noisier with the cages installed. On average the error was also larger (average error 8.6 dB) than the 'equally' divided training/testing groups.

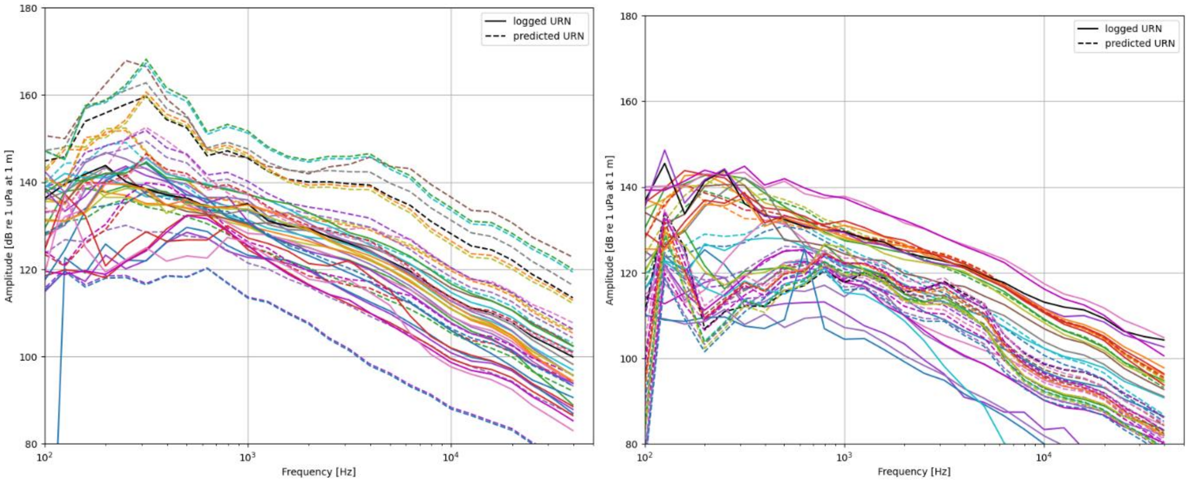

Figure 6-5 Testing results for model trained on No-Cage data and tested on Cage data (left), and for the model trained on Cage data and tested on no-cage data (right).

The second approach of training with data from three of the boats and testing with the data from the fourth boat generated the results in Figure 6-6. Using this approach, the following was observed:

- On average the error was 12.1 dB. *This Is It's* URN was generally over-estimated (average error of 7.7 dB) by the URN TF, while Just Once was generally well estimated (average error 5.8 dB) by the URN TF. Bay Bliss was generally underestimated (average error 7.6 dB). Brooklynn and Boys was a less consistent pattern, but was overall overestimated (average error 5.5 dB).
- This suggests that there is a lot of variation within the class of Cape Islanders and that a larger number of Cape Islanders would need to be included in the training set before the model can generalize to other members of the Cape Islander class without specifically measuring their URN records for inclusion in the dataset.

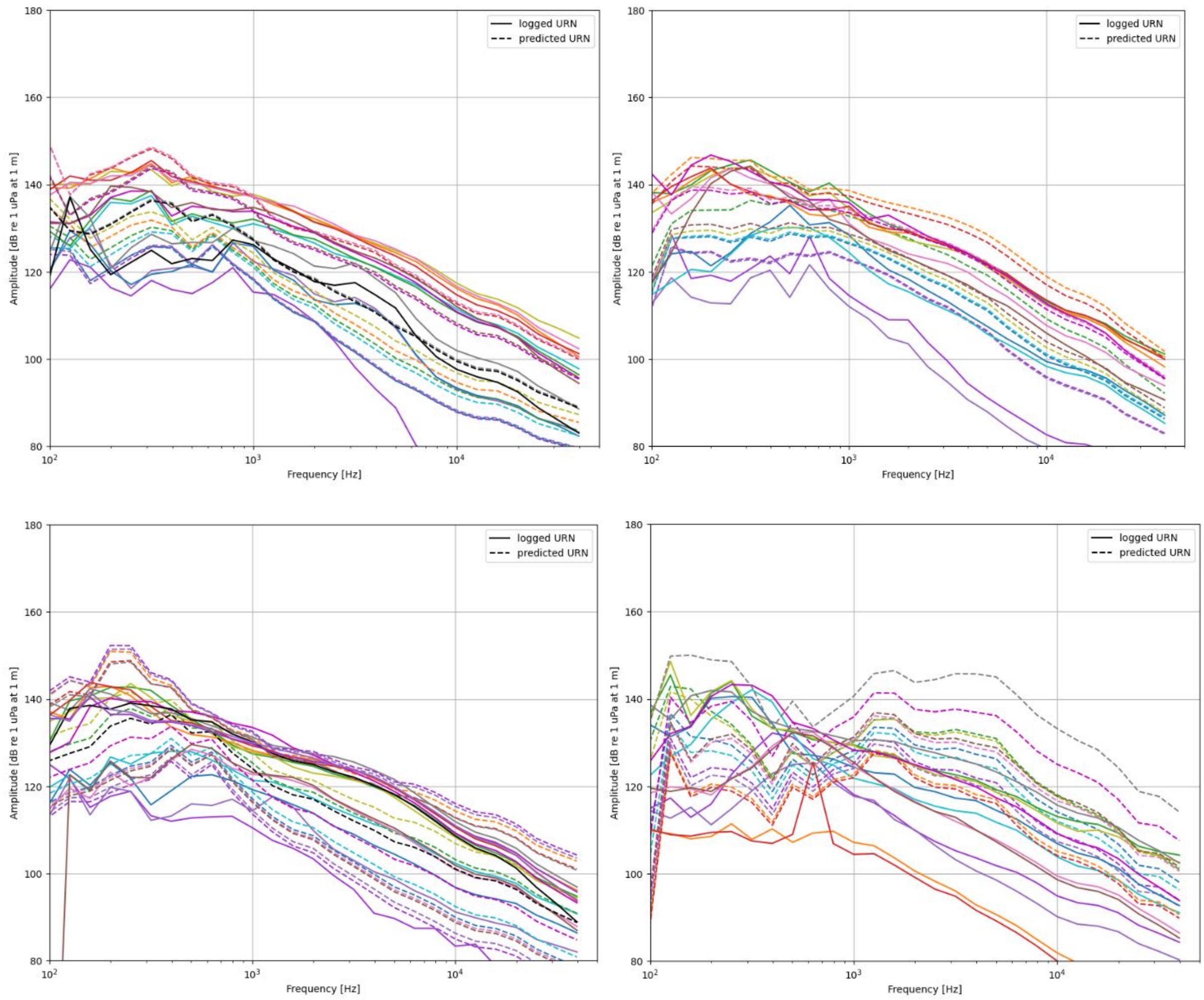

Figure 6-6 Testing Performance results by vessel. Bay Bliss (top left), Brooklynn and Boys (top right), Just Once (bottom left), This Is It (bottom right).

7. Conclusions

This report shows that a small number of sensors can predict the URN for a small marine craft – in this case a Cape Islander – with acceptable performance (~ 5.1 dB error). The minimal instrumentation package comprised only two sensors: one accelerometer located on the hull above the propeller providing vibration RMS velocity between 10 and 100 Hz, and a tachometer measuring the shaft RPM. The URN predictor also required the current season (calculated from the date) to be input as well as the year the vessel was built, and the engine horsepower.

Given these requirements, we identified some options for simple and inexpensive components to make up the CBM instrumentation package. The recommended system includes a Raspberry Pi 4 Model B as the computer, a Pi-SPi-8AI Raspberry Pi Analog Input Interface board as the DAQ, a 4-20 mA accelerometer and a Honeywell Hall-effect Sensor to measure RPM. In total, the cost of this instrumentation package is under $500 CAD. This cost is based on ordering only enough components for one package, thus lacking any efficiencies of scale. The prototype instrumentation package was assembled, and field tested, and the user interface was developed.

The use of such components for CBM on small marine craft to predict URN in-situ is not well established. As a result, a trial plan was developed to record data from fishing vessels using both the prototype instrumentation package as well as the more traditional instrumentation package used in the previous project's trials (especially the DAQ and IEPE accelerometers from NI), and URN to be able to compare the performance using data collected under each system. Trials were completed using the prototype CBM system on the 4 selected boats in September-October 2023.

The data from the trials was processed to evaluate the ability of the prototype CBM system to predict URN from the vessels of this class. The CBM system was shown to produce an average error of 5.1 dB when trained on the 2023 trial data set. However, the inability to apply the model learned on 2020/2021 records to the 2023 trials indicates that data used to train the model must be obtained using consistent measurement methods. The use of data record separation techniques other than by general randomization for training and testing was shown to increase the error in the predicted URN for the Cape Islander class. The sensitivity of the data separation approach suggests that there is a lot of variation within the class of Cape Islanders and that a large sampling of Cape Islanders would need to be included in the training data set before the model can generalize to other members of the Cape Islander class without including their URN records.

8. Performance Indicators

Progress against performance indicators is given in the table below for each activity as listed in Schedule B.1 (Project Description) of the contribution agreement compared to the start of the Project.

Table 8-1 Performance Indicators

Activity	Progress
Activity #1: Establish the underwater radiated noise transfer function methodology for small marine craft	
Hold a kick-off meeting and periodic meetings	Kick-off Meeting 6 May 2022. Progress Meetings held.
Run an analysis of existing underwater radiated noise datasets	Completed
Collect in-water measurements of representative class member vessels	Completed. Trials completed in Oct. 2023.
Run an analysis of tailored datasets	Completed
Develop a progress report	Interim Report March 2023
Activity #2: Develop a low-cost condition-based monitoring sensor package prototype	
Run a preliminary component selection and procurement	Completed. Procurement after April Progress meeting.
Design a web-based user interface	Completed
Iterate and work-up the condition-based monitoring sensor package	Completed
Select final components	Completed
Draft a user guide for the condition-based monitoring sensor package	Completed. Included in Final report Appendix A.

Develop a progress report	Interim Report September 2023.
Activity #3: Verify the condition-based monitoring sensor package and the underwater radiated noise transfer function for type of fishing vessel	
Define trials plans	Completed
Run in-water trials on (at least) two small craft vessels	Completed. Trials for 4 boats completed Sept. – Oct. 2023.
Analyse collected data for system verification iterations	Completed
Activity #4: Final reporting and dissemination	
Develop final report	Delivered March 22, 2024.
Disseminate Project results	Expected to initiate when the report is approved by TC.

9. References

[1] A. Deeb and M. L. Seto, "A methodology to define underwater acoustic radiated noise norms for small commercial vessel classes using neural networks," in *International Conference on Underwater Acoustics (ICUA)*, Southampton, UK, 2022.

[2] K. P. Murphy, "Feedforward neural networks (multilayer perceptrons)," in *Machine Learning: A Probabilistic Perspective*, Cambridge, Massachussetts, The MIT Press, 2012, pp. 563-579.

[3] Lloyd's Register ATG, "Underwater Radiated Noise (URN) and Green House Gas Reduction Program for Canada's Inshore Fishing Craft Milestone 5 Report," Martec Report TR-22-23, Prepared for Graphite Innovation & Technologies under Conntract to Transport Canada - Quiet Vessel Initiative, Halifax, Nova Scotia, 2022.

Appendix A Draft CBM System User Guide

Technical Memo

Project Title: AGREEMENT FOR MITIGATION OF RADIATED NOISE OF SMALL MARINE CRAFT USING CONDITION-BASED MONITORING

Contract No: Contribution Agreement No. 164607

LR ATG Control No: PRJ11100379887

Prepared by: Ken MacKay

Date: 22 March 2024

Re: DRAFT C-1 Condition Based Monitoring System User Guide

1. Introduction

This document describes the setup and use of the prototype C-1 Condition Based Moniting (CBM) system used for the prediction of underwater radiated noise (URN) for small marine vessel – Cape Islander Class. The C-1 CBM system is a cost-effective instrumentation package using a class URN transfer function to inform a vessel operator of the vessel's current predicted URN levels based only on 2 sensor inputs (engine RPM and hull vibration) and boat specifications. The C-1 CBM system was developed through a contribution agreement with Transport Cananda.

2. System Components

The CBM system comprises both software and hardware components as shown in Figure 2-1.

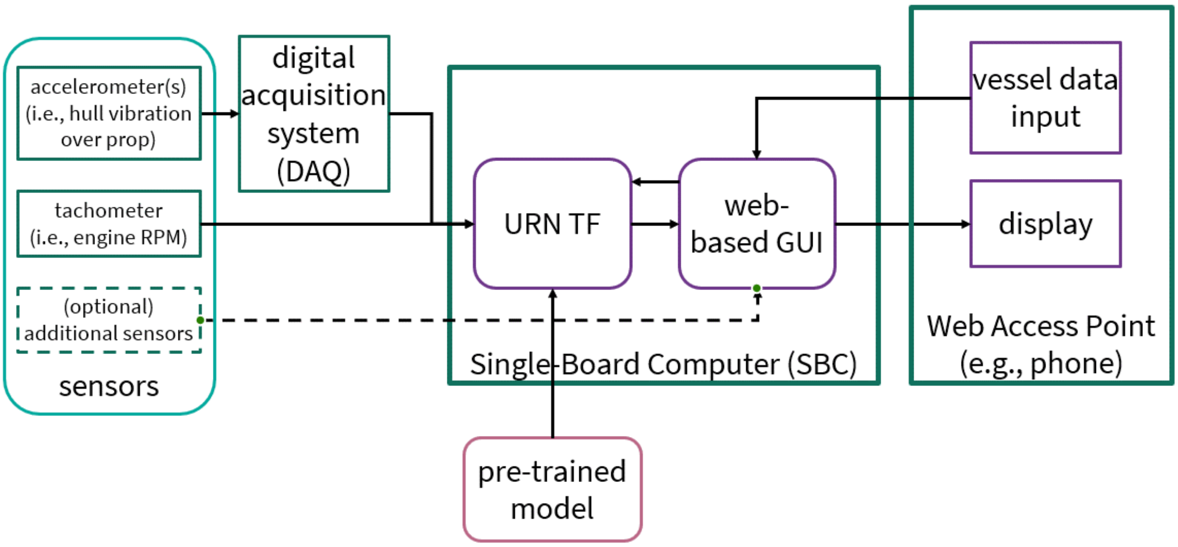

Figure 2-1 CBM System Overview

At the core of the CBM software is a class URN transfer function used in-situ to calculate the URN decidecade spectrum based on sensor measurements and boat parameters.

On the hardware side, the components can be divided into three groups: the sensors, the data acquisition and processing system (in this case a single-board computer (SBC)), and a web enabled device such as a smartphone or laptop through which the operator can view and interact with the CBM system via local networking.

The hardware components of the system consist of a Raspberry Pi Model 4B 8GB SBC and a Pi-SPi-8AI+ DAQ unit mounted in a plastic enclosure (Figure 2-2). Power for the these components are provided through two 110V AC power adapters supplying 5V and 12 V DC.

The system uses a Honeywell 103SR13A-1 Hall effect sensor for measuring shaft rpm and a Wilcoxon PC420-VR-50 4-20 mA Accelerometer for monitoring hull vibration. The yellow cable is attached to the Wilcoxon 4-20 mA accelerometer and input A5 of the Pi-SPi-8AI+ DAQ unit. The grey cable is attached to the Honeywell Hall Effect sensor used as a tachometer and connects to input A1 of the Pi-SPi-8AI+ DAQ unit. The sensor cable connections are permanently attached to the Pi-SPi-8AI+ DAQ unit.

A web access point is not provided with the system, but any Wi-Fi enabled device with a JavaScript enabled web browser can be used.

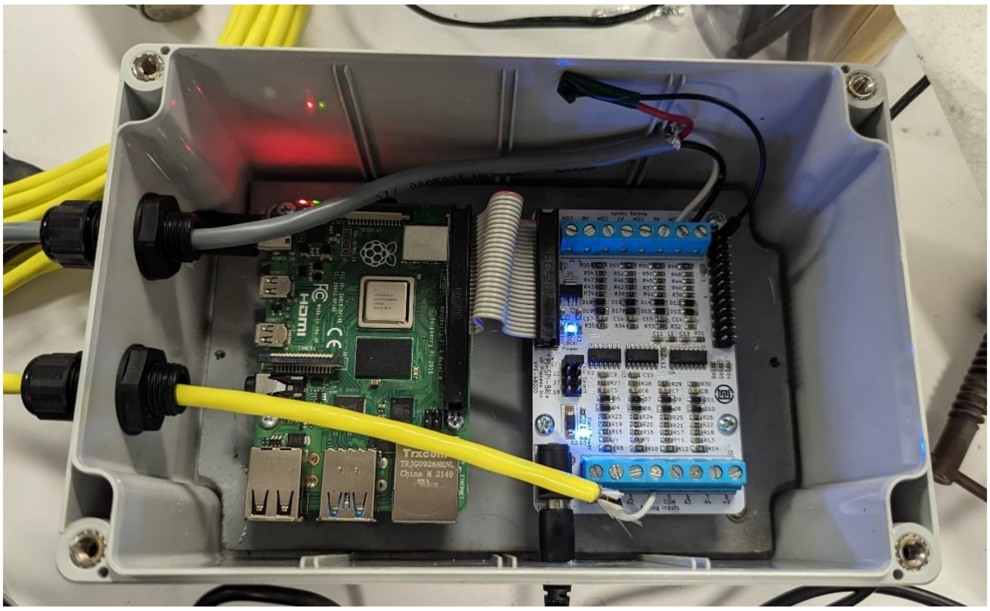

Figure 2-2 CBM C-1 Prototype Internals. Left: Raspberry Pi 4B. Right: Pi-SPi-8AI+ Raspberry Pi Analog Input (4 - 20 mA) Interface. The Hall effect sensor connects to the Pi-SPi-8AI+ via the grey cable. The vibration sensor connects via the yellow cable.

The CBM system works by digitizing sensor outputs with the Pi-SPi-8AI+ interface and processing them with the Raspberry Pi.

Sensor outputs are continuously read, timestamped, and logged to a database by a Python script running on the Raspberry Pi. There is a data processing script running in parallel to the data reading and logging script which accumulates buffers of the last 1000 outputs read and logged from the tachometer and accelerometer. These buffer points are used to determine average propeller shaft RPM and vibration velocity RMS of the hull above the propeller over the buffer duration, which are then input to the URN prediction transfer function along with boat specific parameters. The spectrum output by the transfer function, along will all transfer function inputs - including the determined shaft RPM and vibration velocity RMS - are also timestamped and logged to the database in a separate table.

Users connect to the CBM system with a web enabled device via a Wi-Fi access point generated by the Raspberry Pi and are served a web app GUI providing control of the CBM system and data plot display from the device's web browser. The processed data buffer and raw sensor data outputs are streamed in real-time from the Raspberry Pi to each connected device via WebSocket ports connected to by the web app GUI running on a device. The GUI has individual tabs for each set of data plot and are detailed in Section 4. These tabs are typically used to verify sensors are operating as expected during setup of the system by inspecting raw data streams.

3. System Installation

System installation is comprised of mounting the sensors and connecting the CBM unit to a power source:

1. Locate the CBM unit.

The CBM unit should be placed in a location that does not expose it to excessive moisture or heat, provides for routing of the sensor cables, and allows for power to be provided (through the supplied power adapters). Typically, the CBM unit would be located in the wheelhouse of a Cape Islander fishing vessel. The supplied power adapters require two 100-240V AC inputs, and output 5.1 VDC for the Raspberry Pi and 24VDC for the Pi-SPi-8AI+ board (there is the option using DC-DC converters to allow the use of 12V or 24V ship electrical system). Figure 3-2 shows the CBM unit temporarily located on the floor of the wheelhouse alongside a power pack providing two 110V AC outlets. The Hall effect sensor cable is 7 m in length and the accelerometer cable is 12 m in length.

2. Install Hall effect sensor and magnet on the propellor shaft.

The hall effect sensor must be mounted such that it can detect the passing of a magnet attached to the shaft. A typical mounting arrangement for the Hall effect sensor is shown in Figure 3-3 and Figure 3-4. The magnet can be attached with a suitable tape. Note that the north pole of the magnet must be facing the sensor as it passes (north pole facing outward from the shaft). The supplied mount for the Hall effect sensor consists of an adjustable arm clamp with the sensor mounted at the end. The sensor face should be within 2-10 mm of the magnet as it passes.

3. Install Accelerometer

The accelerometer should be mounted on the hull directly above the propellor (this can be referenced from the rudder stock). The sensor has a 1/4-24 threaded hole that would allow it to be mounted using a stud of the same size attached to the hull. Alternatively, for temporary installation, a magnet with a threaded insert can be attached to the base of the accelerometer, which in turn can be attached to a small steel plate (e.g. a large washer) glued to the hull. A typical mounting arrangement for the Hall effect sensor is shown in Figure 3-5.

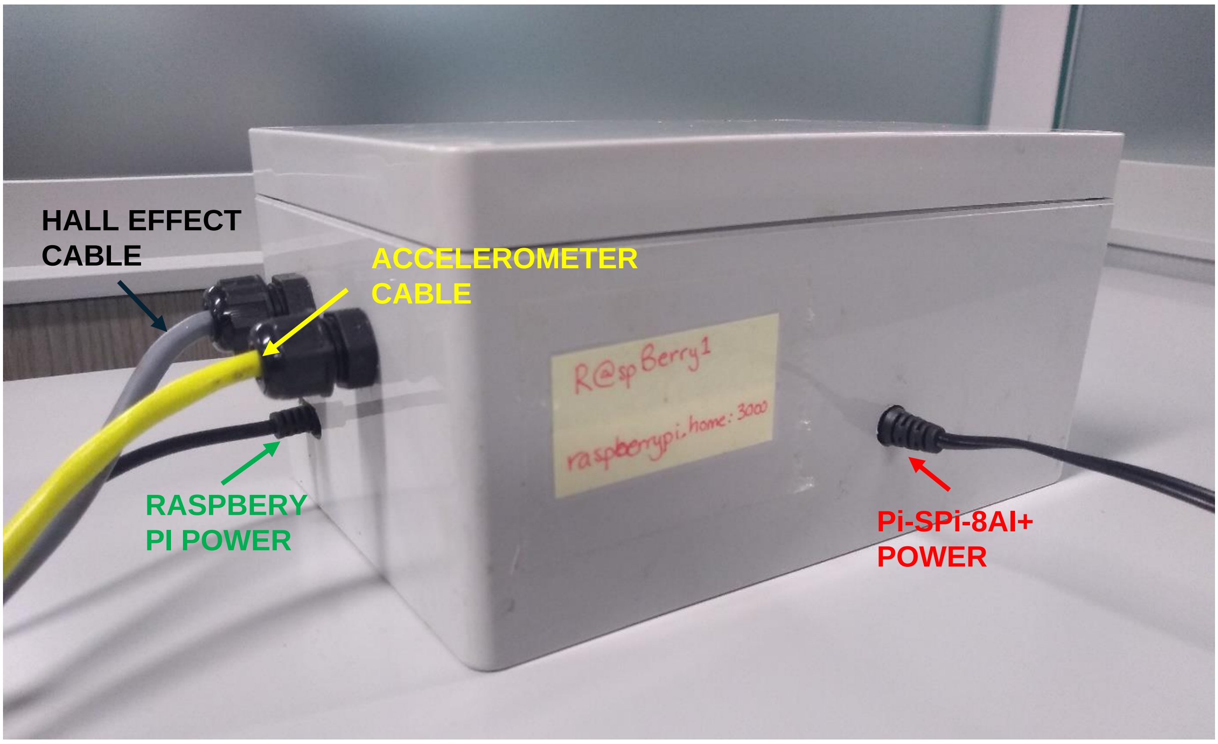

Figure 3-1 Assembled C-1 CBM unit. Red arrow is the Pi-SPi-8AI+ DAQ power connection. Green arrow is the Raspberry Pi power connection.

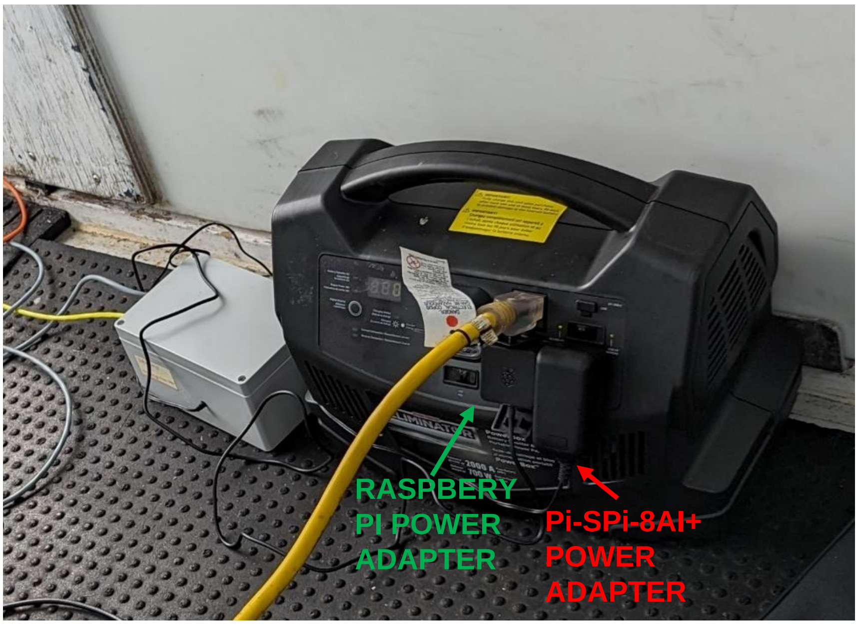

Figure 3-2 CBM system in-situ on a fishing boat trial powered from a portable power pack.

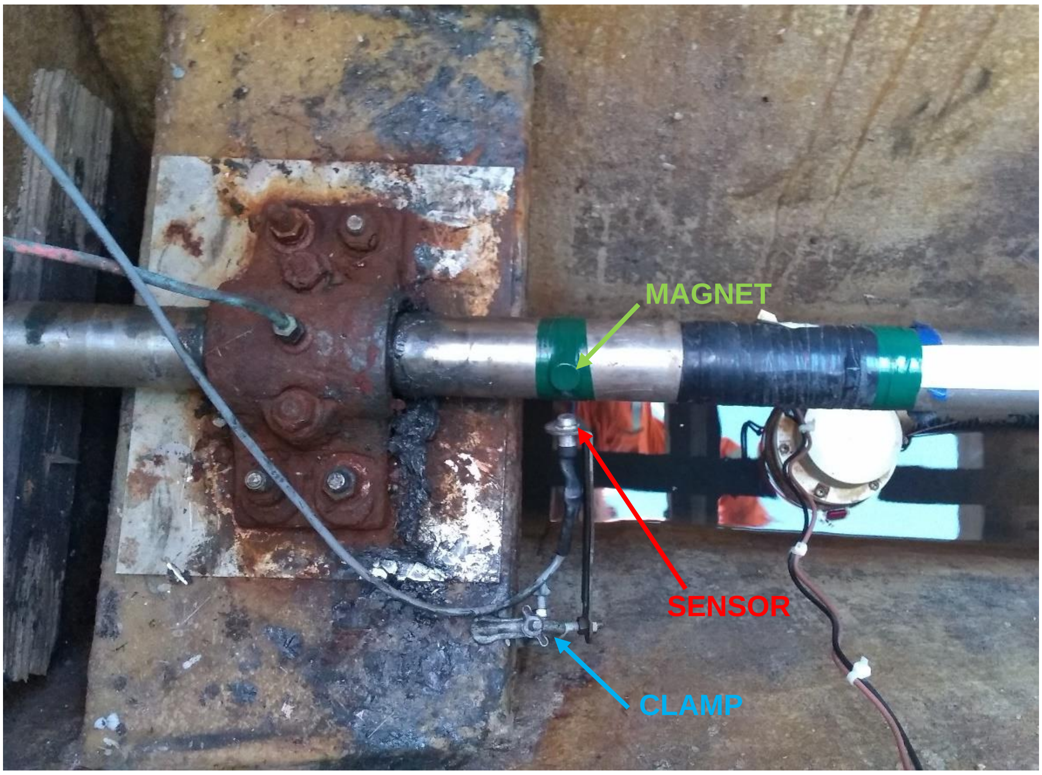

Figure 3-3 Hall Effect Tachometer mounted to hull pointed towards propeller shaft with tachometer triggering magnet taped to shaft.

Figure 3-4 Close up of Hall Effect Tachometer and triggering magnet (attached with green electrical tape to propellor shaft).

Figure 3-5 (Left) CBM 4-20 mA Wilcoxon Accelerometer (yellow cable) mounted on hull above a fishing boat propeller. (Right) IEPE Accelerometer with magnetic base installed.

4. Web App Setup

The web app provides the interface to the CBM system. The web app GUI is accessed by connecting a suitable device (smartphone, tablet, laptop) to the Wi-Fi access point generated by the Raspberry Pi (SSID “raspberrypi”, password “R@spberry1”). Once connected to the access point, open a JavaScript enabled web browser and visit the domain “raspberrypi.home:3000”. The browser will load the GUI and will appear similar to that shown in Figure 4-2. The GUI consists of several tabs accessible through the buttons at the top of the screen. Each of these tabs will be described below.

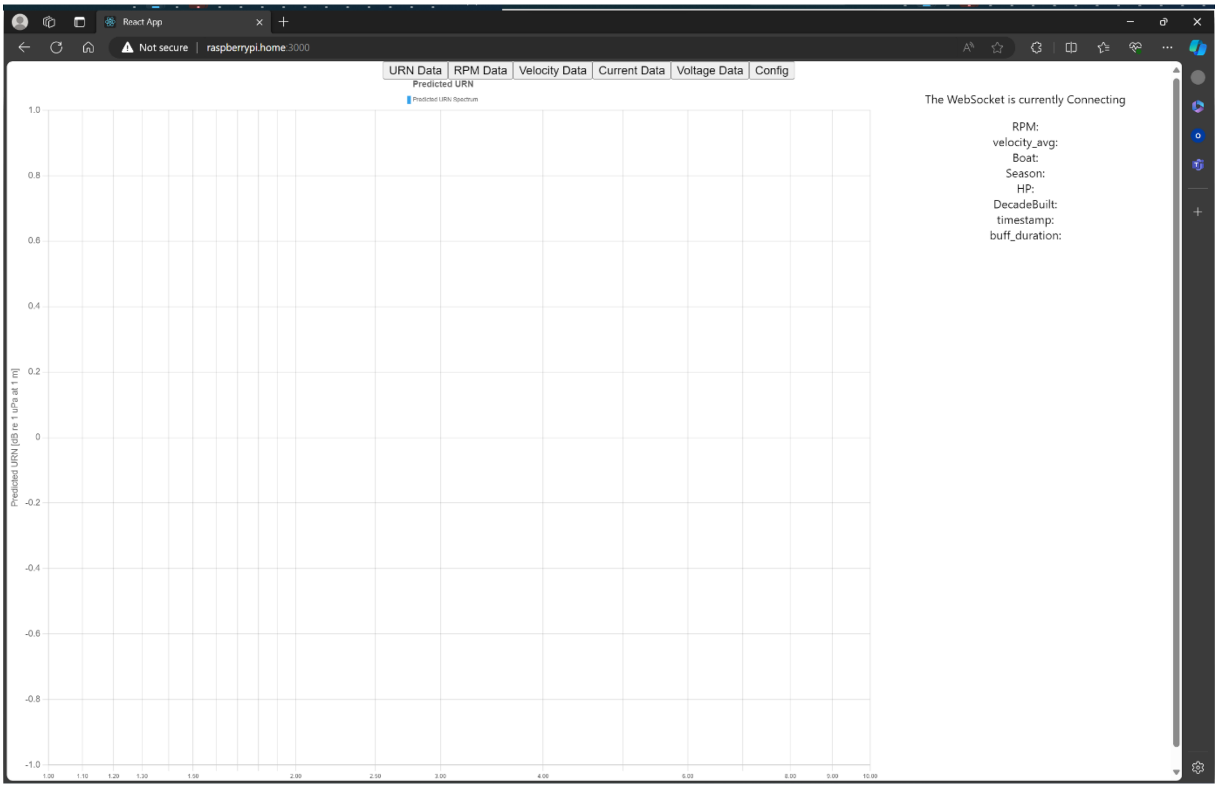

Figure 4-1 The web app GUI upon first connecting to the domain raspberrypi.home:3000, displaying the message “The Websocket is currently Connecting” on the right. This message will change to “The Websocket is currently Open” once the connection to the sensor data webserver is established.

Config Tab:

The URN transfer function requires boat specific parameter inputs, such as as draft, propeller characteristics, engine horsepower, and date of build. The parameters used by the data processing script for the transfer function can be set in the GUI as seen in Figure 4-2. The dropdown menu contains boat parameter presets for a select number of boats, as well as an option to add custom boat data if the need arises.

The “Set Time” button syncs the Raspberry Pi system clock to the clock of the device accessing the web app. This button was included to ensure accurate datalogging timestamps while lacking a real-time clock (RTC) module on the Raspberry Pi. Without an RTC, the Raspberry Pi will not keep time between power cycles and normally relies on internet connectivity to sync its clock. Since the CBM system does not connect to the internet, an external clock source such as one provided by a smartphone or laptop is necessary.

The “Download Data” button will begin a download of the SQLite database used to log all raw and processed data in the web browser.

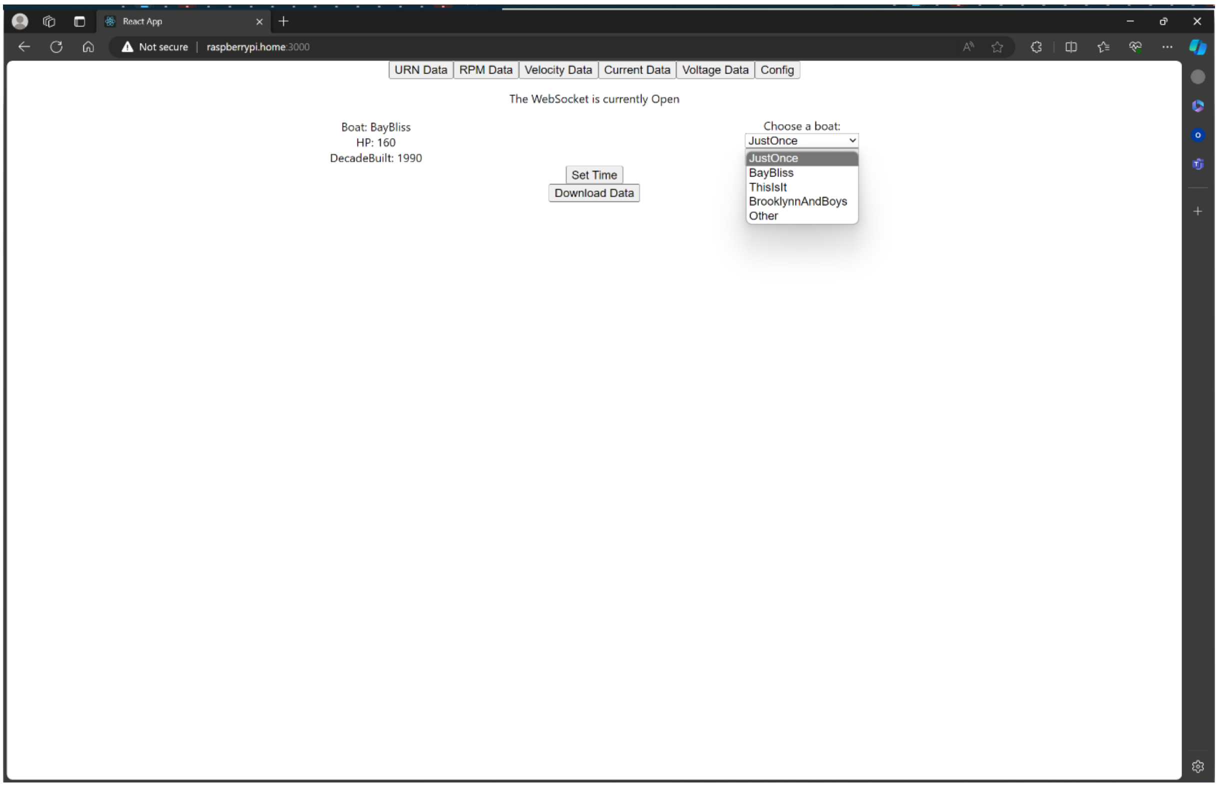

Figure 4-2 Config tab: boat parameter input interface in the web app GUI.

URN Data Tab:

The URN data tab provides the predicted URN emitted from the vessel in decidecade sound levels in dB (ref 1 µPascal at 1 metre) as received in real-time from a processed data buffer WebSocket stream. Figure 4-3 shows an example of the output by the URN transfer function. The input parameters for the transfer function that were used to make the prediction are displayed to the right of the plot.

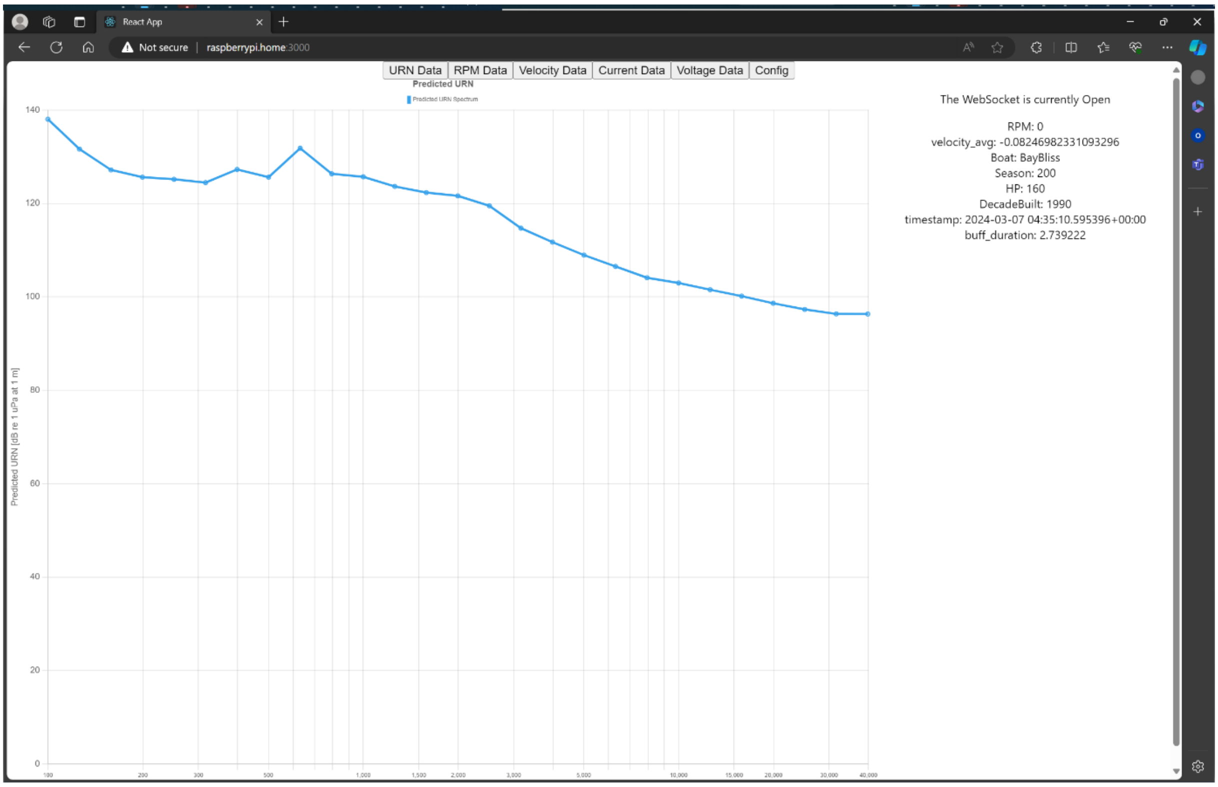

Figure 4-3 Predicted URN plot by the web app GUI as determined by processed tachometer and accelerometer inputs and boat specific parameters.

RPM Data Tab

The RPM Data tab of the Web app GUI (Figure 4-4) displays a plot of the 1000-point buffer of Hall effect (tachometer) voltage data along with the trigger points (when magnet passes by sensor, the “X” symbols indicate in the plot) found via a peak finding algorithm. The software uses the average duration between trigger points over the duration of the data buffer to determine the average shaft RPM. The calculated RPM is displayed to the right of the plot along with the timestamps, buffer duration and boat parameters.

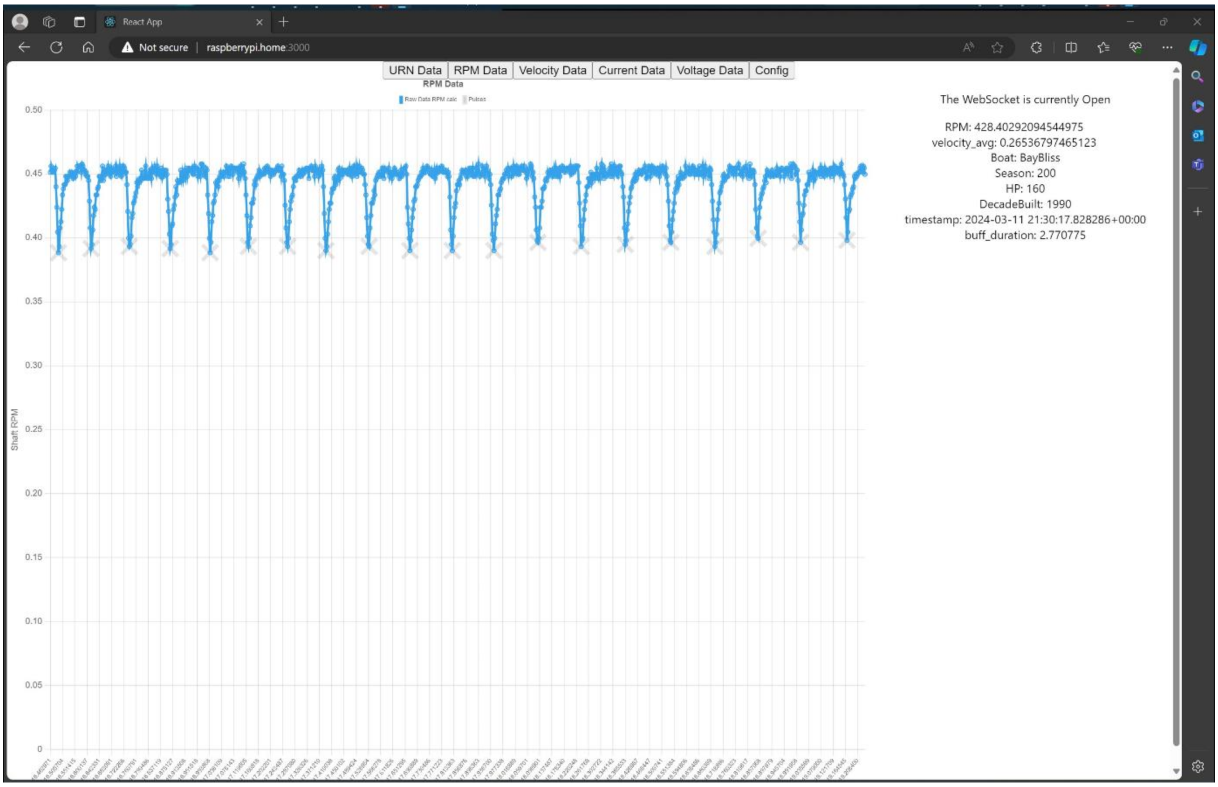

Figure 4-4 Web app GUI displaying a plot of the 1000-point data buffer of tachometer voltage data along with the peaks found via the peak finding algorithm used to determine average shaft RPM over the duration of the data buffer.

Velocity Data Tab

The Velocity data tab shows a plot of the vibration velocity calculated from accelerometer current values received via a raw sensor output data WebSocket stream from the Raspberry Pi.

Vibration velocity is calculated from current measurements taken from the Wilcoxon accelerometer. The accelerometer outputs a current between 4-20 mA that maps to an RMS velocity of 0-127 mm/s. This current is digitized by the Pi-SPi-8AI+ and read by the sensor reading script on the Raspberry Pi, it is then written to the raw sensor data table in the database, sent to the data processing buffer, and streamed to any device running the web app connected to the raw data WebSocket port. The current is averaged and converted to mm/s RMS in the data processing buffer and logged in the processed data table.

The numeric values and timestamp of the last received raw data message over the WebSocket port are displayed to the right of the plot. The maxArrayLength input field controls how many data points received from the WebSocket will be displayed in the plot before they are overwritten. The default is 120 data points. Data older than the specified number of points is removed from browser memory.

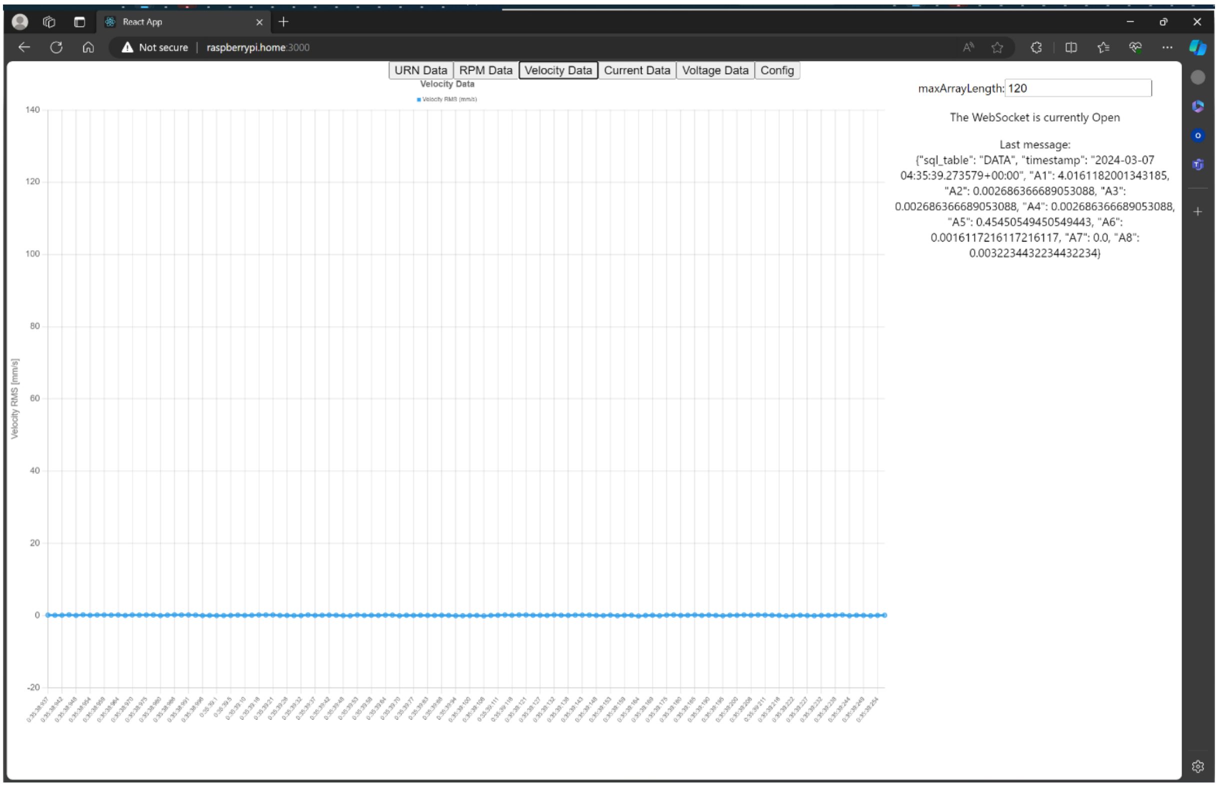

Figure 4-5 The Velocity Data Tab of the Web app GUI plotting a real-time stream of velocity RMS values calculated from the current measured from the Wilcoxon accelerometer.

Voltage Data Tab

The Voltage Data Tab (Figure 4-6) plots voltage data read from the four voltage input channels (A5 through A8) of the Pi-SPi-8AI+ streamed via the raw data WebSocket port. Channel A5 is used to measure the voltage output of the Hall effect sensor (tachometer).

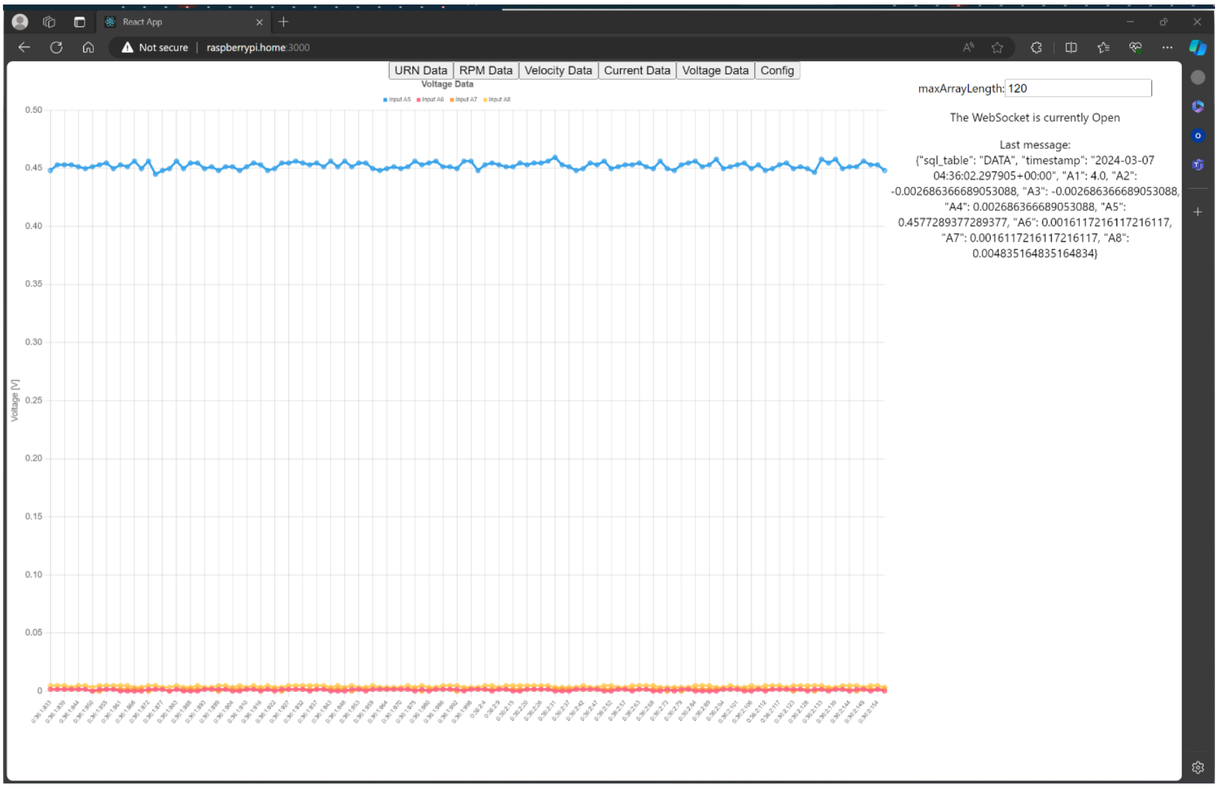

Figure 4-6 Screenshot the Voltage Data Tab of the GUI web app plotting a real-time stream of voltage data read from the Pi-SPi-8AI+ (channels A5 through A8). Input A5 is the output read from the Hall effect tachometer. The tachometer was experiencing no pulses and a steady voltage high output of 0.45 V.

Current Data Tab

The Current Data Tab (Figure 4-7) plots the current data read from the four current input channels (A1 through A4) of the Pi-SPi-8AI+ streamed via the raw data WebSocket port. Channel A1 is used to measure the current output of the Wilcoxon 4-20 mA accelerometer.

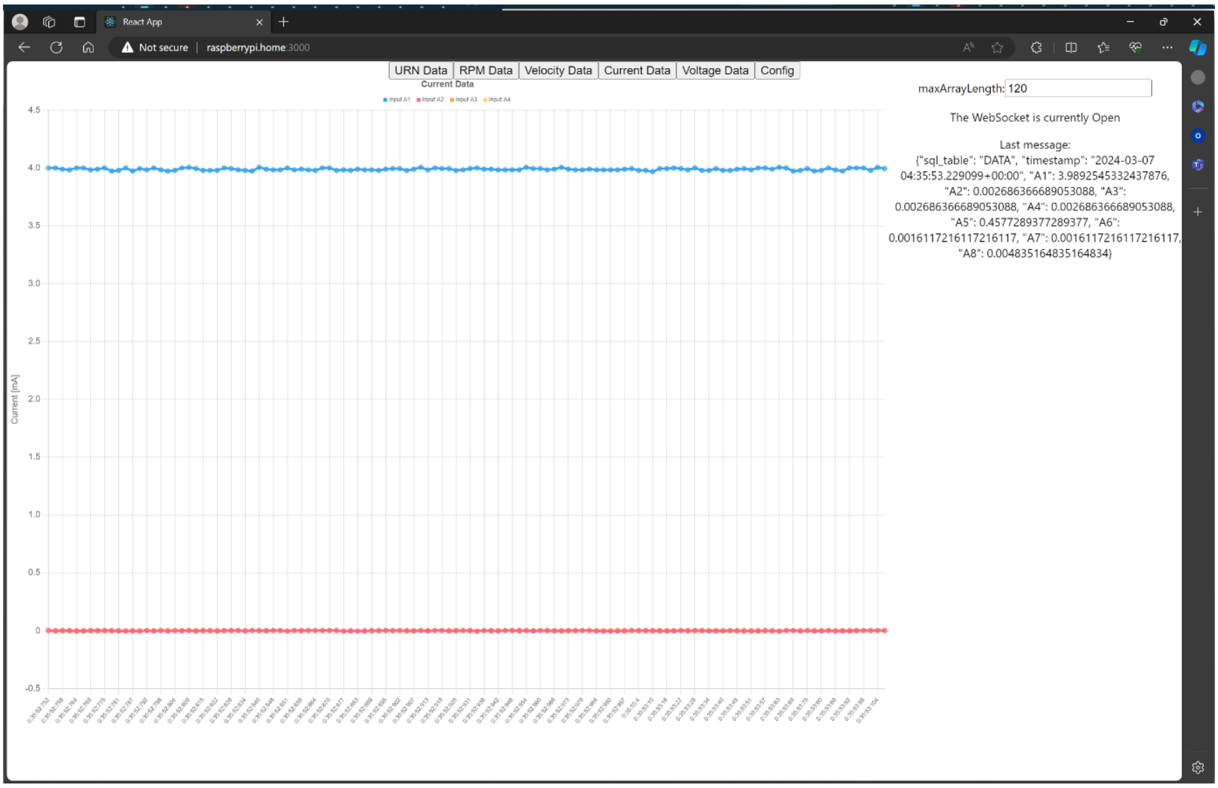

Figure 4-7 Screenshot the Current Data Tab of the web app GUI plotting a real-time stream of voltage data read from the Pi-SPi-8AI+ (channels A1 through A4). Input A1 is the output read from the Wilcoxon 4-20 mA accelerometer.

Ken MacKay
Lloyd's Register Applied Technology Group
237 Brownlow Ave, Suite 200
Dartmouth, NS B3B 2C7
Canada

Registered name Martec Limited

t: 902-880-4098
e: Ken.MacKay@lr.org
w: lr.org