A Report

On

A Machine Learning Based Model for Estimating Ship Noise in Indian Ocean Region

By

Ashutosh Khandal,

Intern at Maritime Research Center, Pune

(6th June – 29th July 2022)

Entry No. 2019ME10781

Mechanical Engineering Student,

Indian Institute of Technology, Delhi

ACKNOWLEDGEMENTS

I would like to express my special thanks of gratitude to my mentor CDR. Arnab Das and Mr. Shridhar Prabhuraman for giving me the excellent opportunity to do this wonderful project in the Underwater domain awareness. Arnab Sir was available at any time to solve any problem or doubt. I am thankful to Arnab Sir and Shridhar Sir for helping me to do this wonderful project successfully. Without their enormous support, it was impossible to complete the project.

Secondly, I would like to thank my college IIT, Delhi to provide me with such an opportunity to work with brilliant people on such a wonderful project.

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ABSTRACT

Underwater Radiated Noise is a major problem for aquatic life. It causes them to lose their acoustic habitat and more often damages their organs. For crew members present on ships and naval platforms also, URN is a major issue. For predicting this noise many mathematical models have been developed. Wittekind model is the recent one and more accurate but it has some drawbacks which are that it requires a lot of parameters that are hard to obtain and requires web scraping. So this makes the model to impractical for use in real-time. Therefore, my project aims to implement a Machine Learning model to predict the output of the Wittekind model with good accuracy by using fewer parameters that are easily available in real-time. Also developing a GUI, so that any user can use my model with their own AIS datasheet to predict the Underwater Radiated Noise.

1. INTRODUCTION

Commercial Ships are the major source of underwater radiated noise which is generated because of the interaction between the hull and water and propeller cavitation which lies in the low-frequency range [1]. Underwater radiated management is an interesting research area. This URN management is important due to some of these reasons, the first is the ship design and manufacturing for efficient operation & maintenance can be performed, and the second is related to the requirement of acoustic stealth for naval platforms to avoid detection by enemy sonars and mines [2], the third is related to degradation of ‘acoustic vision’ of underwater species like marine mammals [10]. Many Underwater species are known to use sound waves for multiple biologically critical functions such as navigation, communication, and survival (through the avoidance of predators) [3]. Their perception of the underwater environment through acoustic signals is called acoustic vision which is seriously degraded because of URN and ambient noise [9]. So, because of these harmful effects on humans, marine mammals, naval applications, etc., we should focus on underwater radiated noise management.

This issue is now getting recognized by the authorities like the International Whaling Commission (IWC), the International Union for Conservation of Nature (IUCN), International Maritime Organization (IMO) for establishing and monitoring rules and regulations [1][4]. So management of underwater radiated noise is necessary. URN management study has broadly covered three main aspects, the first is the measurement & analysis that needs some effective and efficient hardware and software [3], and the second is the prediction of a URN based on available inputs for varied design and operational conditions [5], the third is the deception where we fake the actual signature of platform [2].

Mainly, we are here interested in the prediction part because actual measurement and analysis need a real setup of ships, hydrophones, etc in the ocean that I am not gonna do. Some Mathematical models are presented by D. Ross, RANDI, Wales-Heitmeyer, SONIC, and Wittekind for estimating shipping radiated noise. But all these models have some drawbacks [2]. Because of that, we need an ML-based approach to estimating the shipping noise accurately and also by using parameters that are easily available in the AIS datasheet or on the marine traffic website.

2. SHIP NOISE SOURCE MECHANISMS

As the ship design advances, for structural optimization and high speed to satisfy market demands, there are vibration and noise increment become a trouble. At high speeds, broadband noise approximately covers the range from 100Hz to several kHz [7]. Noise from shipping originates from several different source mechanisms. These sources are mainly categorized into 3 different classes [6]:

2.1. PROPELLER NOISE

The most efficient and dominant source of Underwater radiated noise is the propeller. Some propeller noise mechanisms are tip vortex cavitation, different types of blade cavitation, hub vortex cavitation, bubble cavitation, sheet cavitation, blade root cavitation, pressure pulses due to wake inhomogeneity at the propeller plane, pressure pulse generated by rotating propeller blades, and singing due to resonance between blade natural frequencies are trailing edge vortices, etc.

Propeller noise is extremely load-dependent as the load is low noise because of pressure fluctuations at the blade and as the load is increasing on the propeller blades the pressure on the suction side becomes low enough for cavitation to occur. The pressure difference between the suction side and the pressure side of the propeller blade at the propeller tips will cause vortices. The strength of these vortices will mainly depend on the propeller blade geometry, the loading on the blade, and the wakefield. These vortices will start to cavitate and will generate the broadband noise of low frequency as the cavitation bubbles implode [6].

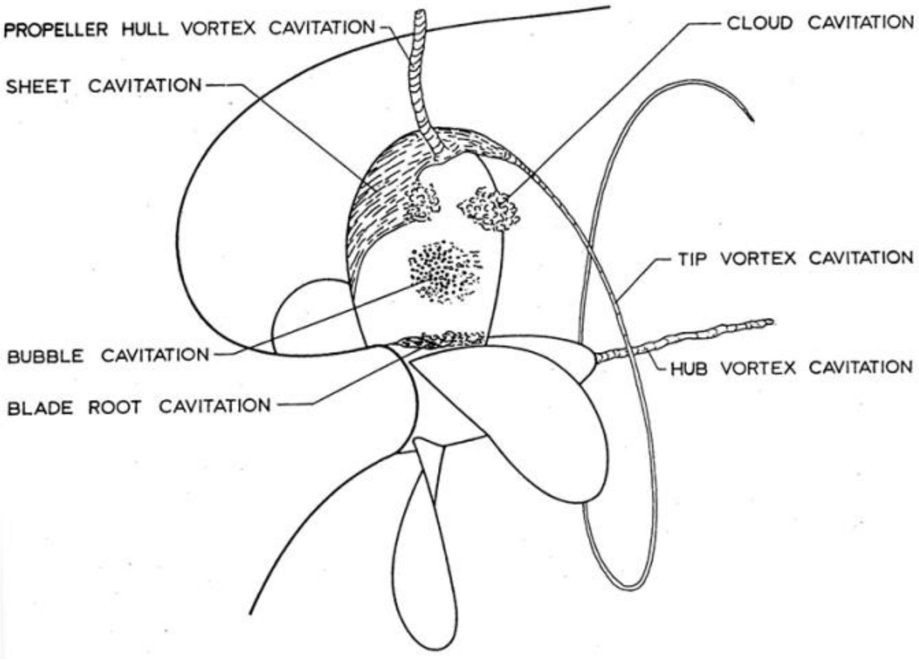

Fig – Different cavitation mechanisms

2.1.2 MACHINERY NOISE

Noise is generated by various machinery devices, mainly by engines (diesel and electric), propulsion, auxiliary system, gearbox, ducts, pipes, turbines, etc. (Devices that are active dynamically placed inside and on the surface of the hull. Machinery noise is generated inside the ship and transmits to water through hull outer bottom plating vibration [6].

Turbines don't generate any noise but after some use, they develop some microscopic defects due to which small pits appear on the surface of intake and the blades which set up eddies in the gas flow, which result in loss of performance and vibrations.

Gear errors and fluctuations in mesh stiffness can cause excitation during gear meshing. This excitation propagates from the gear shafts to the bearing, excites the gearbox, and generates reducer noise which is radiated from the surface of the gearbox.

Here are some **Transmission** Paths for transmitting machinery noise [8]:

- **Structure-borne** path: Sound propagates through the ship structure in form of Vibrations.
- **Fluid-borne** path: Noise transmits through the fluid flow from ducts, pipes, etc to the hull in form of hydro-acoustic pressure fluctuations.
- **Air-borne** path: The pressure field in the Ship compartment can radiate external seawater through the hull.

2.1.3 HYDRODYNAMIC NOISE

This noise is generated because of the interaction of the hull and appendages to the water. Hull itself as well as the appendices attached to the hull will generate turbulence and shed vortices when moving through the water and may sometimes generate significant noise, particularly at high speed. When fluid is in contact with the hull or appendages then at the region close to the hull part, the flow is turbulent and turbulent eddies are the cause of noise and vibration of the hull [6].

3. SHIP NOISE MANAGEMENT

The URN management is a very important research area to achieve acoustic stealth by the naval platform is of major importance; maintaining a low level of URN by commercial ships to comply with regulatory norms to contain acoustic habitat degradation. In URN management we need to focus on the topics: **Source-Path-Receiver** Modelling, **URN measurement and analysis,** and **Prediction or Estimation** of URN using existing models or AI or ML-based models.

The **source-Path-Receiver** model is extremely critical for URN management [2].

- The source, i.e., radiated noise from the platform under varied machinery configurations has unique manifestation and can substantially vary based on the running machinery regime.
- Path, the underwater medium particularly in the tropical littoral waters of the Indian Ocean Region (IOR), further adds to the complications due to the high random fluctuations.
- The receiver also adds to the challenges concerning ambient noise at its location, sensor-related issues, and also signal processing-related complications.

3.1. MEASUREMENT AND ANALYSIS

For measurement of the URN, first, we need to determine measurement parameters like Sound pressure level, One third octave band, Propagation, transmission loss, radiated noise level, range, and reference distance [2].

Now, some measurement systems are [2];

1. Permanently installed ranging facilities
2. Bottom Moored Hydrophones with a support vessel.
3. Surface Supported Hydrophones with a support vessel.
4. Near Shore Measurement.

Some measurement systems are based on vessel systems, some are static systems and some are drifting systems. There are some measurement requirements also like Test site Requirements, Test site water depth, and Background noise [2].

After taking measurements with the help of hydrophones (sensors), we have to analyze the measured data [5]. Analyzing the measured noise data is the post-processing step/phase to account for background noise, bottom effect correction, sensitivity adjustment, distance correction, and transmission loss [5][7].

3.2 PREDICTION OR ESTIMATION OF URN

There are broadly two categories of Mathematical models for estimation of underwater radiated noise: One is Computational which is based on numerical analysis and the second one is the Empirical model which is based on a statistical analysis of noise data.

3.2.1. COMPUTATIONAL MODELS [2][8]:

Some computational models are:

- **Computational Fluid Dynamics**

  it is the branch of fluid mechanics that uses numerical analysis to solve problems that involve fluid flows. It involves using computers to simulate the fluid flow and their interaction with the surfaces using appropriate boundary conditions. The CFD method is one of the most advanced computational tools that can give more insight into flow physics. It can be very useful in predicting and visualizing flow characteristics around the hull and appendages, generating the wake field in which the propeller operates. Depending on how various turbulence scales are modeled, CFD could be classified as (1) Reynolds-Averaged Navier-Stokes (RANS) method or Unsteady RANS (URANS) method, (2) Delayed Detached Eddy Simulation (DDES); and (3) Large Eddy Simulation (LES). Only the last two methods have the potential to resolve a variety of length scales of turbulence structures in the wake of the hull and propeller. The vorticity and turbulence structures in the wake of the hull and propeller may give a significant contribution to the broadband noise, even if such sources are less efficient sources than propeller cavitation and non cavitating blade tonals. Further, the hull wake is very important for the cavitation dynamics. Therefore it is crucial to resolve these structures for a high-fidelity CFD method aiming to predict a wide spectrum of tonal and broadband noise. For the computation of the unsteady flow around the propeller, the unsteady flow around it has to be stimulated first [9]. Once the flow around the propeller is solved, acoustic computations are performed to predict the radiated noise.

- **Propeller Analysis Method**

  Propulsion is generated with the help of a propeller which is one of the major contributors to underwater radiated noise. Many methods are having different accuracy and computational time. Most commonly used are: Momentum Theory, Blade Element Theory, Blade Element Momentum Theory, Lifting line method, lifting surface method, panel method and Reynolds averaged Navier Stokes.

- **Finite Element Analysis Method**

  Mathematical equations are used to describe these phenomena, usually, the Partial Differential Equations which when solved for unknowns in the whole volume of the system is called Finite Element Analysis and when solved only for the unknowns in boundaries is called Boundary Element Analysis. The FEM is used to describe the dynamic behavior of the structure, while the BEM is used to represent the surface acoustic loading on the structure. Here, the focus is on the Machine Learning model, so I am not going to discuss these computational models in detail.

- **Statistical Energy Analysis**

This is a method for predicting sound and vibration through complex structural and acoustic systems. To solve a noise and vibration problem with SEA, the system is partitioned into several components (such as plates, shells, beams, and acoustic cavities) that are coupled together at various junctions. Then vibratory modes of each section are analyzed individually and then collectively. System parameters are expressed in probabilistic terms, and the objective of an analysis is seen to be the prediction of the ensemble-average behavior of sets of grossly similar realizations of an archetypal system

3.2.2. EMPIRICAL MODELS [1]:

Some empirical models are described below:

- **D. ROSS**

Ross model represents the source spectrum level S(f), where f is the frequency at which we want noise, S_0 as a baseline spectrum, together with a ship-dependent shifting of that spectrum S_0 which is determined by logarithms of the ship parameters,

$$S(f) = S_0(f) + S_0$$

The primary basis for this model development is the extensive measurement data from WW2. Analysis of basic noise source generation mechanisms, primarily propeller cavitation, was also taken into account in the model. The base spectrum:

$$S_0(f) = 20 - 20 \log_{10}(f)$$

It is remarked that this expression is reasonable for ships at service speed and frequencies above 100Hz. For lower frequencies, there is more vibration in the measured spectra.

$$S_0 = 134 + 60 \log10(V/V_{ref}) + 9 \log_{10}(D_T)$$

Where reference speed V_{ref} = 10 knots and D_T is the displacement in tons.

- **RANDI**

RANDI Contains a ship source spectrum model which is an adaption, or further development, of the Ross models described above. In this section, the RANDI source spectrum model is given. The ship parameters used in the model are the shipping speed and the ship length. The spectrum consists of three terms,

$$S_{RA}(f) = S_0(f) + S'(V,L) + S''(f,L)$$

S_0 is the RANDI base spectrum and S' is the scaling based on ship parameters. The third term, S" is the small correction term which is only non-zero for low frequencies (approximately below 200Hz). The base spectrum is given by:

Wales-Heitmeyer

The model proposed by Wales and Heitmeyer seeks to reduce the RMS error of the classical Ross Model. The paper argues that the Ross model cannot describe the surface interaction propagation effects observed in the radiated noise spectrograms for some of the larger ships. Instead of using ship parameters as inputs, the WalesHeitmeyer model uses extensive noise data of ships.

$$\overline{S}(f) = 230.0 - 10\log(f^{3.594}) + 10\log\left(\left(1+\left(\frac{f}{340}\right)^2\right)^{0.917}\right)$$

Wales-Heitmeyer divides the source spectrum into two parts: 50-400 Hz and 400-1200 Hz. The justification given for this is that for frequencies above 400 Hz the source spectra showed a simple power law dependence, conversely, for frequencies less than 400 Hz, many of the source spectra exhibited a more complex frequency dependence and there was much greater variability in the spectra across the ensemble.

Keeping these points in mind, a rational spectrum model is proposed in the paper. This model gives a better estimation of both the individual spectra and the variability than the Ross Model, as claimed by Wales and Heitmeyer in their original paper.

Wittekind

This model proposed by Wittekind (2014), estimates noise radiated by individual ships by using ship-specific parameters as input. The total source level consists of three contributions: low-frequency propeller noise contribution (SL1), high-frequency propeller noise contribution (SL2), and machinery noise contribution (SL3). So, the total Source Level (SL) is:

$$SL = 10log_{10}(10^{\frac{SL1(f_k)}{10}} + 10^{\frac{SL\ \ (f_k)}{10}} + 10^{\frac{SL3(f_k)}{10}})$$

Here, f_k is the center frequency for the kth frequency band. The expression for SL1 is obtained by a curve fit to data from Arveson and Vendittis (2008) and leads to the following expression.

$$SL1 = \mathbf{\Sigma}_0^5\ (C_n * f^{\,n}) + A(V,V_C,C_B) + B(D_T)$$

Where V_c is the cavitation-inception speed, C_B is the ship hull block coefficient, and the coefficient values of C_n are: $C_0 = 125$, $C_1 = 0.35$, $C_2 = -8 \times 10^{-3}$, $C_3 = 6 \times 10^{-5}$, $C_4 = -2 \times 10^{-7}$ and $C_5 = 2.2 \times 10^{-10}$. The last two expressions are scaling with speed and displacement respectively:

$$A = 80 * \log_{10}(4 * C_B * V/V_C)$$
$$B = 20/3 * \log_{10}(D_T / D_{T,\,ref})$$

For the high-frequency cavitation noise, SL2 is again obtained from a curve fit to experimental data:

$$SL2 = -5 * \ln f - 1000 / f + 10 + B(D_T) + C(V, V_C, C_B)$$

The function C models speed influence and is given by:

$$C(V, V_C, C_B) = 60 * \log_{10}(1000 C_B V/V_C)$$

For the machinery engine noise SL3, the expression is written below:

$$SL3 = 10^{-7} f^2 - 0.01f + 140 + D(m,n) + E$$

Here, D is a factor modeling the influence of engine mass and the number of engines, and the expression is given by:

$$D = 15 \log_{10} m + 10 \log_{10} n$$

where m=engine mass (tons), n=number of operating engines

The term E refers to the Mount parameter of the engine. E = 0, corresponding to an engine “resiliently mounted” and, E = 15, corresponding to the engine “rigidly mounted.”

DRAWBACKS OF MATHEMATICAL MODELS

Computational Models are highly accurate as compared to empirical ones but these methods required a lot of computations and take time to give the result. Therefore for research purposes, these methods are good enough but impractical for use in monitoring in real-time [1].

Empirical models consider the propeller cavitation as the major source of underwater radiated noise, so if the shipping speed is less than the cavitation inception speed then results are inaccurate [4]. Wales-Heitmeyer models give inaccurate results at low frequencies [2]. Wittekind models require a lot of parameters and some parameters are obtained by web scraping which takes a lot of time and becomes a cause of slow execution. D. Ross's model is inaccurate for modern ships and has a slow execution speed because of the time complexity of O(n) [1].

4. MACHINE LEARNING

Machine Learning (ML) can be defined as a level of algorithm which may allow software applications to create more accurate forecasting output without being externally programmed [11]. Machine learning algorithms use historical data as input to predict new output values. Machine learning has been adopted in many industries like healthcare, finance, agriculture, cyber security, marketing, and Transportation. Now, ML is starting to rise in the shipping industry and a lot of research is done to incorporate Machine Learning into the various domain of maritime. Machine Learning allows us to apply intelligent algorithms and evaluate data that help to guide the logic of possible problems in the maritime area [14].

Here, the role of Machine learning is to predict the ship noise using fewer parameters that are easily available also in the AIS datasheet. The mathematical model for shipping noise estimation presented by Wittekind is more accurate and more advanced as compared to other mathematical models, but the problem is that Wittekind models require a lot of parameters that are hard to obtain and require web scraping like engine mass, number of engines, mount parameter of the engine, block coefficient, displacement, etc. So, here my job is to use fewer parameters, that are easily available, to predict the ship noise. Here, I am using a deep learning-based approach – Deep Neural Networks.

4.1 DEEP LEARNING

Deep Learning is a subset of Machine Learning. Deep learning is part of the broader family of machine learning methods based on neural networks with representation learning. Deep-learning architectures such as deep neural networks, deep belief networks, deep reinforcement learning, recurrent neural networks, and convolutional neural networks have been applied to fields including computer vision, speech recognition, natural language processing, machine translation, medical image analysis, climate science, etc.

Artificial Neural Networks are a subset of machine learning and are at the heart of deep learning algorithms. Artificial Neural Networks were inspired by information processing and distributed communication nodes in biological systems (like in the human brain). The adjective "deep" in deep learning refers to the use of multiple layers in the network. Neural networks are a set of algorithms that are designed to recognize patterns. These patterns are numerical, so all real-world data like images, sound, text, time series, etc. must be converted into numerical values.

Neural Networks are made of layers and these layers are made of nodes. A node or neuron is a place where computation happens. A node combines input from the previous layer after applying weights to each input. In the node, the product of input & weight are summed and then the activation function is applied to that sum to determine whether and to what extent that signal should progress further through the network to affect the overall output.

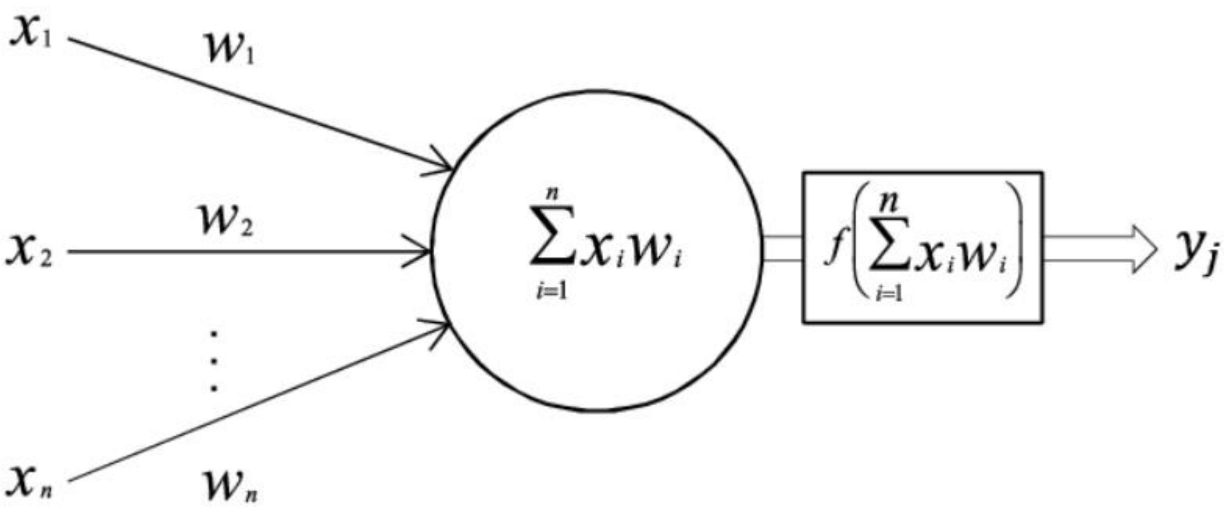

Fig – how nodes of Neural Network Layer look like

(Reference - https://www.researchgate.net/figure/a-The-building-block-of-deep-neural-networks-artificial-neuron-or-node-Each-input-x_fig1_312205163)

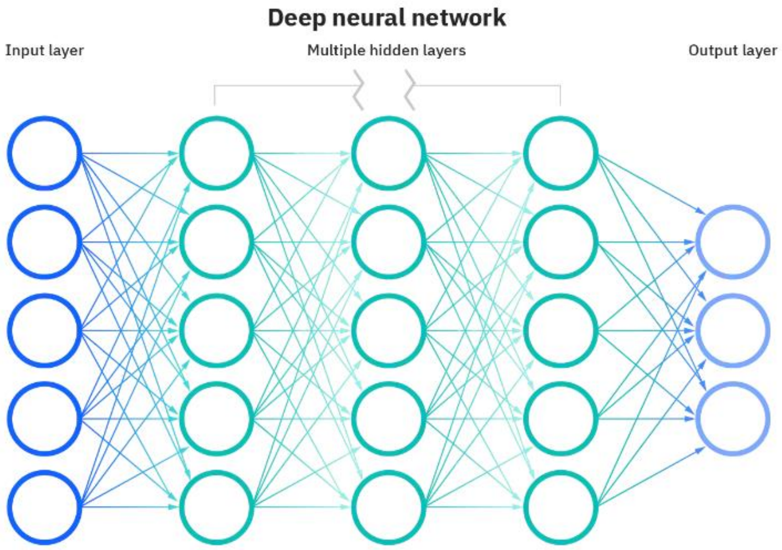

Fig – Layers of Neural Network

(Reference - https://www.ibm.com/cloud/learn/neural-networks)

Each layer of node trains on a distinct set of features based on the previous layer's output. The further you advance into the neural network, the more complex the features your nodes can recognize since they aggregate and recombine the features from the previous layers. This is known as Feature Hierarchy, and it is a hierarchy of increasing complexity and abstraction. It makes deep learning networks capable of handling very large, high-dimensional data sets with billions of parameters that pass through nonlinear functions.

We pass the input parameters into the input layers. Initially, weights are randomly initialized to a small number close to 0 but not 0 then these parameters go through each layer as discussed above, and then at the output layers, Output is stored. Then it will calculate the value of the loss or cost function. Neural networks try to minimize this loss function as this loss function is generated by comparing predicted results and expected results. Then this loss or error is backpropagated from right to left in the neural networks and weights are updated in such a way that the cost function tends to be minimum. This is called backpropagation. How the weights are updated is decided by the optimizer. Optimizer helps to adjust the weights efficiently and to get results faster. The overall task is to adjust the weights accordingly so that the loss will be minimal and we get a good prediction.

METHODOLOGY

In this problem, to estimate the shipping noise in the Indian Ocean Region, I used an Artificial neural network approach. I used the Ship Length, Ship Speed, Ship Deadweight, Ship Type, and Frequency as input for the ANN model. The output parameter is the Ship Noise. So, my first task is to get the dataset for training and testing the ANN model, so I used the Wittekind model for calculating the noise value of ships. I got the input parameters for the Wittekind model from the AIS datasheet and MarineTraffic website through web scraping. Then extract the desired input and output as discussed above from that data.

Now, come to the ANN, the first task of data preprocessing is a very important step. Data preprocessing include importing dataset, encoding the labeled data, splitting data for training and testing, feature scaling, etc.

DATA PREPROCESSING

Import that dataset and split the input and output using the pandas library. Then I used the label encoding for ship type as Neural networks understand only numerical values, we have to just do the encoding for data, which is not numerical, to convert into numerical values and this encoding is done by using Scikit-Learn Library.

One important thing is Skewness, if our data is skewed then we won't get an accurate result and this can lead to underfitting or overfitting of data. So, for that, I checked the skewness of data and use the power transform (using the box-cox method) to remove the skewness of data.

After that, I split the data into training and testing with a test data size of 0.2 percent of the total data. After that, I used the Standscaler from Scikit-Learn Library for feature scaling purposes. Feature scaling is very important because not all input parameters are in the same range, and because of that Higher range input parameters will get high weight and the ANN model lead to the wrong result in that case.

BUILDING ARTIFICIAL NEURAL NETWORK

After completing the Data Preprocessing step, I build the ANN layers. Here, in this problem, I made the 5 hidden layers and put 11 Nodes in each hidden layer. As my problem is regression, I used 1 node in the output layer.

TRAIN ARTIFICIAL NEURAL NETWORK

After completing the ANN building steps, now it's time to train the artificial neural network model. At the time of training, we need an optimizer for the faster solution and a loss function that will tell us how accurately our model is predicting the result.

- **Loss Function:** To decrease the predicted noise and expected noise, I used the Mean Squared Error loss function which needs to be minimized to get accurate predicted results.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

MSE = mean squared error

n = number of data points

Y_i = observed values

$\hat{Y}_i$ = predicted values

- **Back Propagation:** For backpropagation and updating weights, I used Adam's Optimizer which is the most commonly used and very efficient optimizer.

5. IMPLEMENTING ANN MODEL

I implement the Artificial neural network model to predict Wittekind's output by taking the parameters which are available in the AIS datasheet. Input Parameters are:

- Frequency
- Ship Speed
- Ship Length
- Ship Type
- Ship Deadweight

Frequency	Vessel Speed	DWT	Vessel Length	Vessel Type	Noise
200	0.2	54019.55148	190	Fishing	172.2859967
50	0.3	460.5936791	51	Tanker	150.0796168
50	0.1	339.0403213	47	Diving	148.7489505
300	0.8	103653.5595	229	Tug	189.1213292
500	10.2	53029.12501	189	Tug	166.2846488
1000	0.5	61.54115999	30	Tug	131.9378438
950	0.5	78.83204227	32	Other	133.5034648
550	0.1	744.3126113	58	Tug	147.1939908
200	2.5	1742.491715	73	Tanker	154.3619633
950	0.1	1573.196688	71	Tanker	146.5042673
100	4.3	1831.841365	74	Tanker	155.6214959
600	16.8	120235.1644	239	Container	183.8155559
100	11.6	22920.90991	149	Other	177.8644436
850	11.3	100540.6291	227	Cargo	165.6545187
900	15.4	99008.94071	226	Other	165.6841796
300	0.1	33593.81389	166	Other	166.2177801
200	6	6.738284271	17	Cargo	130.3985662

Fig – Snippet of data that was used to train the ANN Model

6. ACCURACY ANALYSIS

Mean square loss for Test data = 3.02 and for train data = 2.96

ANN model is tested with 2105 test data. Results are analyzed in terms of the difference b/w Predicted Noise and Expected Noise:

- The difference is less than or equal to 1dB: for 1405 data (Accuracy = 66.74%)
- The difference is less than or equal to 3dB: for 2006 data (Accuracy = 95.29%)
- The difference is less than or equal to 5dB: for 2044 data (Accuracy = 97.10%)
- The difference is less than or equal to 9dB: for 2094 data (Accuracy = 99.47%)
- The difference is less than or equal to 14dB: for 2105 data (Accuracy = 100 %)
- The difference is less than or equal to 18dB: for 0 data

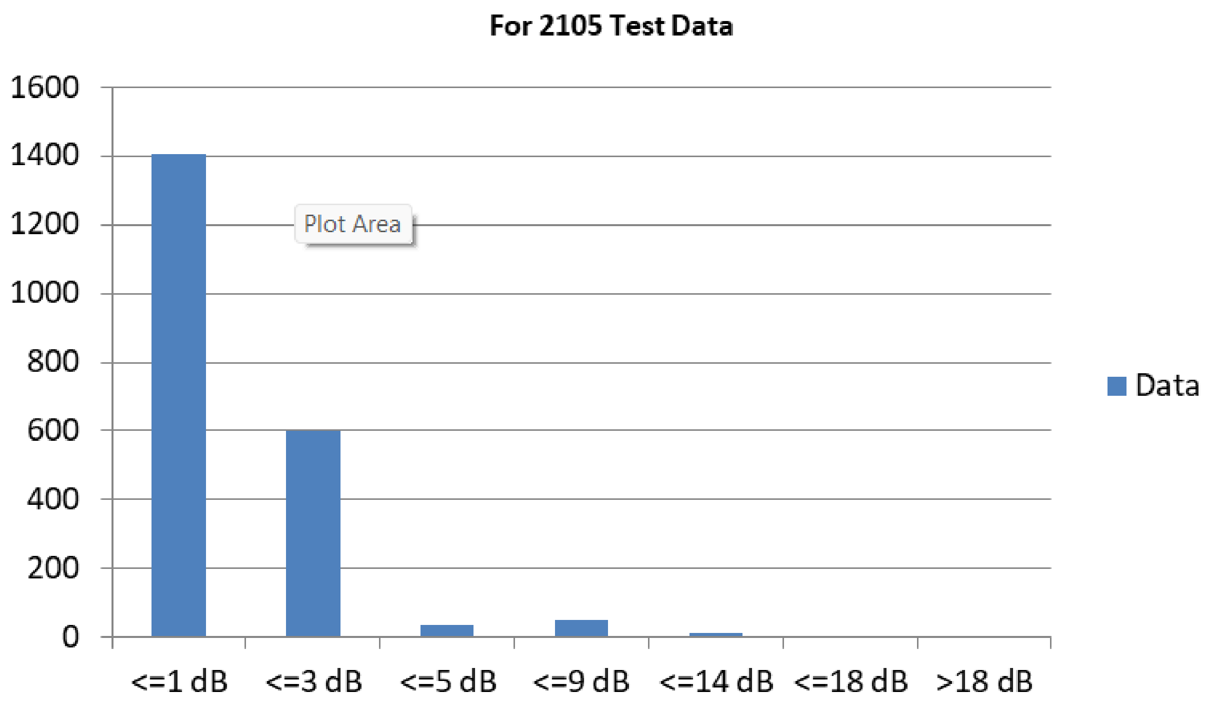

Fig – Bar Graph is showing the number of predictions on the Y-axis and the difference b/w predicted and actual noise on X-axis.

7. GUI DEVELOPMENT

After completing Machine Learning based model for estimating shipping noise, I developed a GUI (Graphical User Interface) that allows the user to run my trained Machine Learning model with their own AIS datasheet to predict the Underwater Radiated Noise. I developed the GUI with help of Qt Designer and PyQt which is a GUI widget toolkit in python.

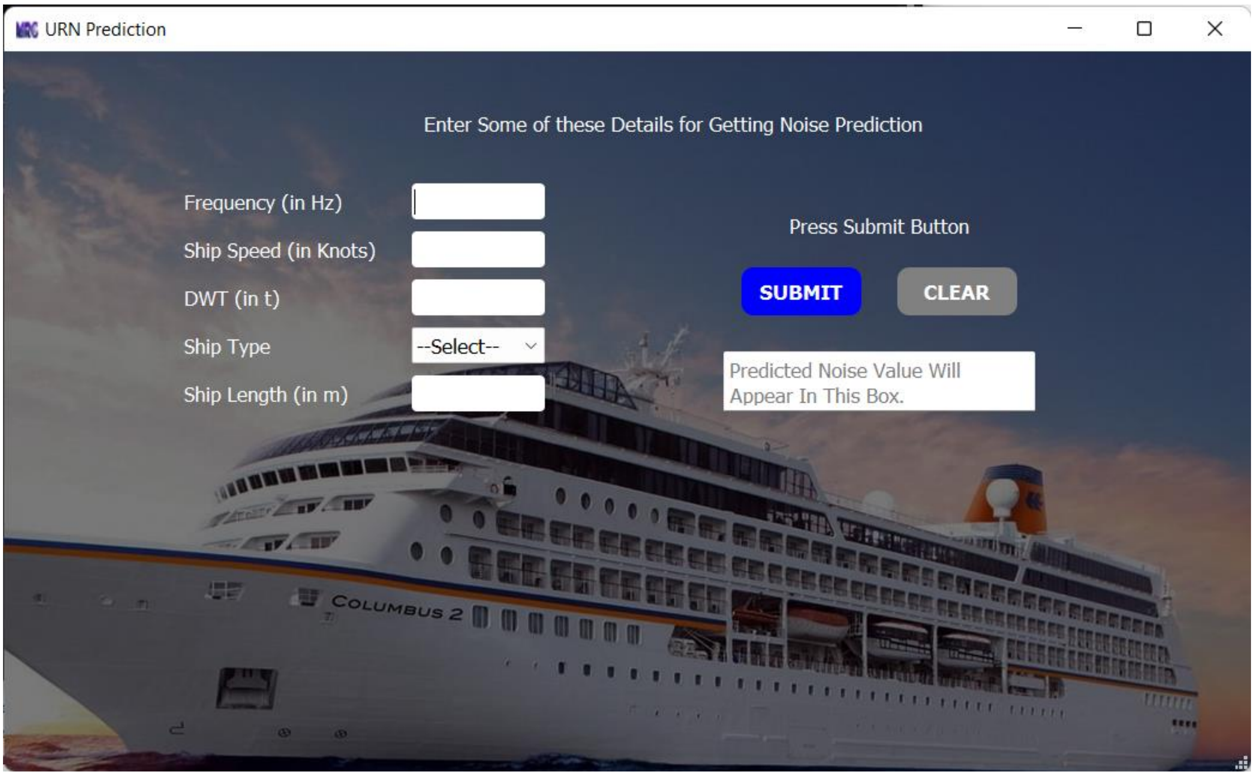

Fig – Snip of Graphical User Interface.

8. CHALLENGES

There are some challenges with the AIS data and estimating shipping noise approaches. Some of them are listed down here:

8.1. Problem with AIS data

As we know, the primary source of information for underwater radiated noise prediction models is the AIS (Automatic Identification System) data. So any problem with AIS data may give a wrong result or no result at all. Some common challenges with AIS data are listed down:

- Commercial vessels below 300GT (gross tonnage) are not fitted with AIS data.
- The accuracy of AIS information received is only as good as the accuracy of the AIS information transmitted.
- AIS data signals can be switched off by the vessel for not giving any information.
- AIS data of warships are not available as this data is sensitive information and not easily available and inaccessible to the public.

8.2. Challenges with Source-Path-Receiver Models

Some challenges with Source-Path-Receiver Models are:

- Sources i.e. Ship Machinery configuration has their unique manifestation and varies based on running machinery regimes.
- Path i.e. underwater channel adds to the complications due to the high random fluctuations.
- The receiver adds to the challenges concerning ambient noise at its location, sensor-related issues, and also signal processing-related complications.

8.3. Challenges with Machine Learning

There are some challenges with Machine learning models. Some of them are listed down here:

- **Data Availability:** Sometimes we use less amount of data to train the Machine learning model which becomes the cause of inadequate learning. So insufficient training data is also a challenge as data is sensitive information and is not available at the public level.
- **Monitoring complexity of model:** artificial neural networks can learn from complex data but because of many hidden layers sometimes learning is a computationally heavy task, so it might lead to slower processing. Also, the challenging task is to choose the optimum number of hidden layers and the number of neurons in each of these hidden layers.

9. FUTURE DIRECTIONS

Many areas require further work to be done in this field including noise models, problems with AIS data, and implementing effective AI or ML models for an easier and faster solution.

1. Open database - As the data availability is one challenge for URN management study, we have to focus on the built up an open database of ship parameters that are required for URN study, this is very helpful for researchers. With a larger dataset, the artificial neural network becomes more accurate.

2. Many limitations of AIS data can be fixed with help of AI or ML like AI can be used to detect whether switching on/off of AIS data is intentional or not, an error in AIS data is because of manipulation of data by human or any other reason.

3. Hardware and Software – As an ML-based model is to be run on ships, so further research may include the optimization of the artificial neural network or other algorithms on the hardware present on ships. Moreover, even this process of prediction can be sped up using parallel computation, if such technology is present on the ship, then it may be leveraged.

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11. CONCLUSIONS

Over the year, many mathematical models have been developed for estimating underwater radiated noise, in those models, D. Ross is the oldest and Wittekind is the recent one. D. Ross is developed at the time of WWII and because of this, the Ross model can't be used for modern ships, and the Wittekind model requires a lot of parameters that are hard to obtain, and requires web scraping, because of that this model is impractical for real-time use. Computational models are very accurate but they require a lot of computational power, which also makes computational models to impractical for real-time use.

Till now, no significant work has been done by using machine learning or artificial intelligence for estimating shipping noise. And we have seen that in many areas, machine learning is already become popular and proved itself very accurate and good. So, here also machine learning can do better than mathematical models. So I used the deep neural network (A machine learning-based method) to predict the Wittekind noise output accurately and using parameters that are easily obtainable in real-time. As a trained ML model can be used on a low-powered computer, this significantly reduces the cost of implementation for monitoring the noise radiated by ships in real-time.