MARITIME RESEARCH CENTER
FOUNDATION FOR UNDERWATER DOMAIN AWARENESS

Research Note

A Machine Learning Model for Estimating Shipping noise in India Ocean Region

Ashutosh Khandal[1], Dr. (Cdr.) Arnab Das[2], Sridhar Prabhuraman[2]
[1]Department of Mechanical Engineering, IIT Delhi
[2]Maritime Research Center, Pune

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 perform, the second is related to requirement of acoustic stealth for naval platforms in order 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, survival (through the avoidance of predators) [3]. Their perception of the underwater environment is through acoustic signals, it called acoustic vision that is seriously degrades because of URN and ambient noise [9].

This issue is now getting recognized by the authorities like the International Whaling Commission (IWC), International Union for Conservation of Nature (IUCN), International Maritime Organization (IMO) for establishing and monitoring rules and regulations [1][4]. Some Mathematical models are present 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. 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], the second is the **prediction of 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].

2. URN MANAGEMENT

The URN management is very important research area in order to achieve the acoustic stealth by naval platform is the major importance; maintain low level of URN by commercial ships to comply with regulatory norms to contain acoustic habitat degradation. In the 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.

Source-path-receiver model is extremely critical for URN management [2].

- The source, i.e., radiated noise from the platform under varied machinery configuration 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.
- Receiver also adds to the challenges with respect to ambient noise at its location, sensor related issues and also signal processing related complications.

2.1 Ship Noise sources and Mechanism

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

2.1.1 Propeller Noise

The most efficient and dominant source of Underwater radiated noise is the propeller. Some propeller noise mechanisms are tip vortex cavitation, blade cavitation, hub vortex cavitation, bubble cavitation, sheet cavitation, blade root cavitation etc. Propeller noise is load dependent as the load is low noise is because of pressure fluctuations at the blade and as the load is increase on the propeller blades the pressure on suction side become low enough for cavitation to occur. The pressure difference between suction side and pressure side of the propeller blade at the propeller tips will cause vortices. These vortices will start to cavitate and will generate the broadband noise of low frequency as the cavitation bubbles implode [6].

2.1.2 Machinery Noise

Noise generated by various machinery devices, mainly by engines, propulsion and auxiliary system, gear box, ducts, pipe etc. (Devices those are active dynamically placed inside and on the surface of the hull. Machinery noise generated inside the ship and transmits to water through hull outer bottom plating vibration [6].

So 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 transmit through the fluid flow from ducts, pipes etc to hull in form of hydro-acoustic pressure fluctuations.

- **Air-borne path**: Pressure field in Ship compartment can radiated external seawater through hull.

2.1.3 Hydrodynamic Noise

This noise is generated because of interaction of hull and appendages to the water. When fluid is in contact with 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 hull [6].

2.2 Measurement and Analysis

For measurement the URN, first we need to determine measurement parameters like Sound pressure level, One third octave band, Propagation and 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 support vessel.
3. Surface Supported Hydrophones with support vessel.
4. Near Shore Measurement.

Some measurement systems are based on vessel system, 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 analyse the measured data [5]. Analysing of the measured noise data is the post-processing step/phase to account for background noise, bottom effect correction, sensitivity adjustment, distance correction, transmission loss [5][7].

2.3 Estimation or Prediction of shipping noise

There are broadly two categories under which estimation models come: The one is the computational which is based on numerical analysis and second one is the empirical models which are based on statistical analysis of noise data.

- **Computational Models [2][8]:**
  - Computational fluid dynamics
  - Propeller analysis method
  - Finite element analysis method
  - Statistical energy analysis
- **Empirical Models [1]:**
  - D. Ross
  - RANDI

- SONIC
- Wales-Heitmeyer
- Wittekind

Drawback or Limitations of these models

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

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

3. MACHINE LEARNING

Machine Learning (ML) can be defined as a level of algorithm which may allow software applications to create more accurate in forecasting output without being external programmed [11]. ML is starting to rise in shipping industry and lot of research is done to incorporate the Machine Learning into various domain of maritime. Machine Learning allows to apply intelligent algorithms and to evaluate data that helps to guide the logic of possible problems in maritime area [14]. Some of recent state of research is given below:

3.1 Classification of Underwater Acoustic Target, 2017 [12]: Hao Yue used the Convolutional Neural Network (CNN) and deep brief network (DBN) for the Classification of Underwater Acoustic Target. The key to underwater target recognition is the feature extraction and outstanding property of Deep Learning is that it can capture the deep features hidden in target signals through multi-level network architecture without structure features designed artificially. They also used traditional machine learning method like support vector machine and WNDCHRM. Then results show that deep learning method can achieve higher recognition accuracy and particularly DBN achieve higher accuracy (96.99%). The one main challenge is here to obtain the audio dataset of underwater targets for training ML model that is difficult.

3.2 Enhance the maintenance process of naval ships, 2016 [13]: Coraddu et al. used machine learning to enhance the maintenance process of naval ships. Author focused on the Regularized least square (RLS) and Support vector machine (SVM) method of machine learning. The performance and potentialities of RLS and SVM models are benchmarked by training them on data to forecast the performance decay of Gas Turbines (GTs, used for vessel propulsion), installed on a naval vessel. Choosing the proper number of data for training and testing purpose was one of the challenging tasks as it has a non-negligible impact on quality of final model. Results show that SVM perform better than the RLS.

3.3 Anomaly Detection in the Maritime Domain, 2014 [14]: Obradovic et al. used support vector machine, neural network, Bayesian network, etc. to carry out anomaly detection in the maritime domain. As the Data source, they used the AIS data. They faced some challenges related to AIS as AIS is provided by vessel, so it can be incorrect information intentionally. They faced challenge of Insufficient training data as the AIS produces vast amounts of data reporting on the information about movements of the vessels, there are no known anomalous tracks.

3.4 Prediction of a Ship's Operational Parameters, 2021 [15]: Kiriakos Alexiou used the Artificial Intelligence Techniques for Prediction of a Ship's Operational Parameters. In this paper the authors compares the performance of multiple regression algorithms like Artificial Neural Network (ANN), Tree Regressor (TRs), Random Forest Regressor (RFR), Linear Regression etc in predicting the output power of the Main Engines (M/E) of an ocean going vessel because M/E power is directly related to Fuel Oil Consumption. As result authors found good coincidence between actual and predicted value of M/E power during the whole range of data set, while linear regression is least accurate approach.

ML or AI has been used in many domains of maritime but yet there has not been done signification work done towards the use of ML for the estimating noise with empirical models. ML can do better than empirical or computational models. ML can be used to reduce the time complexity of empirical models and can be used to estimate the radiated noise by giving fewer parameters.

Like for Wittekind model, some parameters are obtained by web scraping that causes of slow execution but ML or AI can help with estimating the noise without taking these parameters.

4. CHALLENGES

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

4.1 Problem with AIS data

As we know, 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 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 switch off by 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 for public.

4.2 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 vary based on running machinery regimes.
- **Path** i.e. underwater channel adds to the complications due to the high random fluctuations.
- **Receiver** adds to the challenges with respect to ambient noise at its location, sensor related issues and also signal processing related complications.

4.3 Challenges with Machine Learning

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

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

5. RESEARCH DIRECTION

There are many areas that require further work to be done in this field including noise model, problems with AIS data, implementing the effective AI or ML models for easier and faster solution.

1. **Implementing an Effective ML based models like Deep Neural Network** for estimating the shipping noise that is able to give output efficiently without taking the much parameters as Wittekind model takes and also able to reduce the time complexity of empirical models. For training deep neural networks, we can use the AIS data and output noise data of Wittekind model as a training data for neural networks as the Wittekind model is better choice among empirical models.

2. **Many limitations of AIS data can be fixed with help of AI or ML** like AI can be used to detect that switching on/off of AIS data is intentionally or not and error in AIS data is because of manipulate data by human or any other reason.

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

4. **Open database** - As the data availability is a one challenge for URN management study, we have to focus on the built up such an open database of ship parameters those are required for URN study, this is very helpful for researchers.

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