Research Note

Estimation Of Shipping Radiated Noises Using AI

Aviral Tyagi, Shridhar Prabhurman & Dr(Cdr) Arnab Das

Commercial ships are the major source of underwater radiated noise[1] which is generated because of interaction between hull and water and propeller cavitation which lies in the low-frequency range[2]. This severely affects marine animals especially baleen whales[3]. This issue is now getting recognized by appropriate authorities like the International Whaling Commission (IWC), International Union for Conservation of Nature (IUCN) and, International Maritime Organization (IMO) for establishing and monitoring rules and regulations. D-Ross, RANDI, Wales-Heitmeyer, SONIC, and Wittekind are models for estimating shipping radiated noises[1]. But except for the Wittekind model, all other models are limited in the frequency range and ship parameters and also, they do not model the familiar hump at approximately 50 Hz of the ship underwater noise spectrum[4]. However, Wittekind has the drawback that some of its parameters are hard to obtain as they are not available from Automatic Identification System (AIS) data and rely on web scraping; delaying the noise estimation. Therefore, to monitor ship noises in real-time none of the models can be deployed. Instead of relying on collecting all parameters Artificial Intelligence (AI) can be implemented to take only the easily obtainable parameters and give the output of Wittekind whereby reducing the time complexity and hence making it deployable.

Estimation Of Shipping Radiated Noises

As ship design advances, particularly with reference to structural optimisation and high speeds to satisfy market demands, there is an inclination for noise and vibration troubles to become extra pronounced. There are various sources of noises and vibrations in ships some of which are[5][6][7][8][9][10]:

- The prime movers - typically diesel engines.
- Shaft-line dynamics.
- Propeller radiated pressures and bearing forces.

- Air conditioning systems.
- Maneuvering devices such as transverse propulsion units.
- Cargo handling and mooring machinery.
- Vortex shedding mechanisms.
- Intakes and exhausts.
- Slamming phenomena.

They can be segregated into[11]:

- Noise generated by devices active dynamically placed inside and on the surface of the hull, mainly by engines, propulsion and auxiliary, and system of transport of mechanical energy-shafting.
- The noise produced by ship propellers.
- Acoustic effects connected with cavitation of propellers and flow around the underwater part of the hull.

The most efficient underwater noise source of the ship is the propeller. One part of its noise is connected with the blade rate, this signal and its harmonics make usually the dominant contribution to low-frequency tonal levels at high speeds of the ship[12].

At higher speeds, a broadband noise covering approximately range from 100Hz to several kHz accompanies the motion of a ship. It is connected with phenomena of cavitation on the propeller and flow around an underwater part of the hull. The features of the spectrum in this frequency range are also influenced by factors depending on the speed of the ship, as for instance setting of the propeller, progress in cavitation, etc[11].

There are broadly two categories under which models to estimate the shipping noises fall. The first is computational which are based on numerical analysis. Second is empirical which are based on a statistical analysis of noise data.

- Computational Models[2]
    - Computational fluid dynamics
    - Propellor analysis method
    - Finite element analysis
    - Statistical energy analysis

- Empirical Models[1]
    - Ross
    - RANDI
    - Wales-Heitmeyer
    - SONIC
    - Wittekind

All computational models are highly accurate compared to empirical models but they have a major drawback which is, they require a lot of computational power and take time to give results. Hence, this makes them suitable for research purposes when designing ships but impractical for use in monitoring real time[13][14].

Empirical models consider propeller cavitation as the major source of underwater radiated noise so they are inaccurate when the speed of the ship is less than cavitation inception speed. Also, Wales-Heitmeyer gives inaccurate results at low frequencies because of Lloyd's effect which is ignored by all other models except Wittekind as it considers three different contributions while estimating total source level. These three are:

- low-frequency propeller noise contribution
- high-frequency propeller noise contribution
- machinery noise contribution

AI

Artificial intelligence is starting to rise in the shipping industry and lot of recent research is being done to incorporate AI into various domains of maritime. Some of the recent state of the art research is given below:

- Obradovic et al. used support vector machine, neural network, Bayesian network, etc. to carry out anomaly detection in the maritime domain[15].
- Dobrkovic et al. used DBSCAN algorithm to determine efficient waypoints for voyage planning by using AIS data[16].
- Coraddu et al. used machine learning to enhance the maintenance process of naval ships[17].

- It has also been used to analyze AIS data to enhance maritime security[19][20] and ship navigation[21].
- Eric L. Ferguson et al. used convolutional neural networks (CNN) to monitor shallow-water environments using a single sensor[22].

Although AI has been used in many domains of maritime yet there hasn't been any significant work done towards the use of AI for the empirical noise models. D. Ross model is inaccurate for modern ships and it has slow execution speed because of the time complexity of O(n)[23]. Moreover, the Wittekind model which is the better choice; requires some parameters that are obtained by web scraping, resulting in slow execution speed as well.

Challenges & Opportunities

As the primary source of information for all empirical models is AIS data, therefore any problem with AIS data will lead to the wrong result or no result at all.
Common problems associated with AIS are:

- Commercial vessels below 300GT are not fitted with AIS.
- It may be switched off intentionally to avoid giving any information.
- Its data transmission is error-prone.
- Data is manually entered so it can be manipulated to give wrong information.

Artificial intelligence or machine learning first learns how to predict which requires time and is a computationally heavy task. Also, the data from which it learns need to be of a substantial amount as fewer data often lead to inadequate learning. Another layer of difficulty is that data is not easily available as it is sensitive information, therefore, most it is classified making it inaccessible for the public.

Research Directions

There are many areas that require further work to be done in this field including noise models, problems addressing AIS data, implementing AI technology to make various tasks easier and faster. Listed below are some of the work which can be taken up to move forward:

1. Empirical models like D.Ross have used data of ships dating back to WWII to develop their model which makes them unreliable for use in today's age. So they need to be modified using data of ships that are currently in service.
2. Many limitations of AIS can be fixed with the help of AI.
    a. It can be used to detect if the switching on/off of AIS is intentional or not.
    b. It can detect if there is any error in AIS data or if there's any human intervention to manipulate the data.
    c. It can be used to locate and fix errors in data transmitted.

3. It can be used to reduce the time complexity of empirical noise models. Moreover, it can be used to estimate the output of the model by giving fewer parameters. Wittekind model is the most recent and is better than the other models but has a drawback that some of its parameters require web scraping, AI can help with estimating the noise without taking these parameters.

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