Advances in the Development of Monitoring Systems Allying Acoustic Real-Time Data and Model Validation for Effective Management of Underwater Noise Pollution

Alessio Maglio
SINAY – Maritime Data Solution
Caen (France)

Fulvio Fossa
RINA Consulting S.p.A.
Genoa (Italy)

Abstract**—**Underwater noise generated by offshore industrial activities poses significant risks to marine life, especially cetaceans. This paper presents an innovative real-time monitoring system combining embedded passive acoustic monitoring, marine mammal detection based on AI, and acoustic modelling to assess and manage underwater noise pollution. The modular system, deployed on autonomous buoys, is equipped with various recorder-hydrophone configurations and supports both real-time analysis and remote human validation. Beyond local measurement, the integration of propagation models allows extrapolation to unmonitored areas, enhancing spatial coverage. Field validations, including live offshore operations, demonstrate the system's reliability, responsiveness, and compliance-readiness under European regulatory frameworks such as the EIA Directive and the Marine Strategy Framework Directive (MSFD). This solution offers a scalable and effective tool to support mitigation actions and timely decision-making to mitigate the acoustic impact of offshore activities.

Keywords— Passive Acoustic Monitoring, Marine Mammals, Underwater Noise, Real-Time Monitoring, Sustainable Development, Environmental Compliance

INTRODUCTION

The rapid expansion of offshore industrial activities has raised critical concerns about underwater noise pollution and its effects on marine life [1]. Many marine species, especially cetaceans, rely on acoustic cues for vital functions including navigation, foraging, and social interaction. Chronic or acute anthropogenic noise can interfere with these behaviours or even cause physical harm. International regulatory frameworks like the EIA Directive and the Marine Strategy Framework Directive (MSFD) in Europe, ACCOBAMS, and various national guidelines have mandated the monitoring, reporting, and mitigation of underwater noise emissions as part of broader environmental impact control efforts.

To address this, Passive Acoustic Monitoring (PAM) has emerged as the principal method for tracking both ambient underwater noise and biologically significant sounds such as cetacean vocalizations [2]. Modern PAM systems now support real-time monitoring and alerting, leveraging advances in communication, embedded computing, and signal processing. However, despite these advances, several technological and operational challenges remain.

Among the most pressing is the development and integration of embedded AI algorithms capable of detecting and classifying a wide range of cetacean vocalizations in real time, across diverse acoustic environments. Power supply supporting embedded data processing and overall system solidity and stability in harsh weather conditions remain open problems. Additionally, acoustic modelling techniques that can extrapolate from measured data to unmonitored areas are needed to provide full spatial coverage and enhance risk management, especially in large offshore operations.

Furthermore, it is worth noting that existing infrastructures such as cabled ocean observatories has been successfully employed to monitor underwater noise and biological activity in deep marine environments. For example, the EMSO (European Multidisciplinary Seafloor and water-column Observatory) network exemplifies this approach, providing long-term datasets from instrumented nodes on the seafloor [3]. These observatories enable high-resolution, multi-parameter data acquisition—including acoustic arrays—for scientific research and continuous environmental assessment.

In parallel, several EU Member States have established or are planning fixed PAM stations deployed on the sea bottom as part of national strategies to fulfil the MSFD Descriptor 11 requirements. These coastal and offshore acoustic stations are intended to characterize baseline ambient noise and track long-term trends in anthropogenic soundscapes across European waters.

However, such fixed infrastructures, whether cabled observatories or national MSFD monitoring nodes, are not designed for the operational constraints of temporary offshore industry activities. Their static deployment, limited geographic coverage, and focus on long-term ecological trends make them less suitable for dynamic, high-risk construction environments. Temporary industrial operations require mobile, scalable, and autonomous systems that can be rapidly deployed and repositioned based on project phases, environmental risk, or operational feedback.

The system presented in this work addresses these constraints through a hybrid solution that combines real-time PAM, autonomous energy management, and model-informed noise extrapolation.

System Architecture and Technical Approach

The system is conceived as a modular, autonomous, and real-time platform for passive acoustic monitoring (PAM) during offshore industrial activities. It is specifically designed to meet the temporary, mobile, and compliance-driven nature of operations such as marine constructions or geophysical surveys, i.e., contexts in which rapid deployment, real-time feedback, and operational integration are essential.

A. Multisensor architecture

At the core of the system is a network of multi-channel and buoy-mounted acoustic modules designed to work autonomously: they can record, process, and transmit data without relying on external support. The approach has been tested with different types of underwater recording equipment, which makes it adaptable to a wide range of projects. For instance, RTsys RESEA units combined with HTI-99 or COLMAR1195 hydrophones have been used successfully; these sensors typically cover frequencies from about 5 Hz up to 180 kHz and higher. Such bandwidth is well suited both to tracking cetacean vocalizations and to monitoring the acoustic footprint of human activities. Depending on the purpose, hydrophones are configured identically or differently: sensitivities around –170 dB re 1 V/µPa are typically chosen for marine mammal detection, while lower values, down to –210 dB re 1 V/µPa, are applied when measuring louder sources so as to prevent saturation and capture reliable levels. Each acoustic unit may host between one and four hydrophones indeed, giving flexibility in the way the array is set up. The data streams are handled in real time, while the raw wav files are systematically archived on local disks to ensure long-term backup. In parallel, the system also supports Ocean Sonics IC-Listen smart hydrophones, which integrate the sensor, the acquisition electronics, and onboard processing in a single device, reducing the amount of hardware needed during field operations.

B. Underwater sound measurement

Each buoy houses an industrial-grade embedded computer (ModBerry), which runs Python-based acoustic analysis software. This software performs local signal processing at ten-second intervals, including broadband noise level measurements (SPL, SEL). as well as third-octave band analyses, or the calculation of power spectral density (PSD). It is also possible to apply bandpass, lowpass or highpass filters, as needed, or to avoid certain ones depending on the use case.

C. AI-Based Cetacean Detection and Classification

A distinguishing feature of the system is its use of embedded artificial intelligence algorithms initially developed thanks to collaboration efforts between Sinay and the University of Caen [4] that perform detection and classification of cetacean vocalizations onboard the buoy. Presently, the AI data processing is based on a ResNet neural network architecture applied to spectrogram analysis. This kind of models simultaneously capture the spatial and temporal patterns of signals to detect delphinid clicks, whistles and whale songs. Each detection is automatically recorded with its type, timestamp, and performance metrics. Overall, Detection Probability has reached 96% with a False Positive rate at approximately 0.005%. The models were verified on a dataset of 7,762 signals, including 762 signals per detection type verified by experts. The 4% of signals that the model fails to detect (false negatives) correspond to very weak signals or signals masked by ambient noise in the area.

D. Detection verification and validation protocol

Despite the deployment of onboard AI, the system architecture maintains a human-in-the-loop verification protocol, which ensures regulatory robustness and operational confidence. For every vocalization event flagged by the AI, an audio sample (.wav) of 2 seconds containing the detection is automatically forwarded either to a remote control centre through the mobile network or to other platforms (e.g. a support vessel nearby the PAM buoys, typically through Wi-Fi connection), where trained operators inspect the data using PAMGuard, a reference software tool widely accepted in the marine bioacoustics community. This approach enables fast alerting while preserving the interpretability and traceability required for environmental compliance and decision-making, such as activating mitigation procedures or delaying noisy operations.

E. Combining measures and propagation models to extrapolate to unmonitored areas

In scenarios where noise source locations are known, it becomes possible to leverage acoustic propagation models to estimate noise levels beyond the locations directly monitored by the system. This is particularly important because underwater noise does not decay uniformly with distance: due to complex propagation effects, such as refraction, reflections, and bathymetric influences, noise levels may rise and fall as one moves radially from the source. As a result, resurgences of high acoustic energy may occur at distances beyond the monitored perimeter, potentially exposing marine mammals to harmful sound levels without detection.

To address this risk, the system supports a hybrid approach in which in-situ acoustic measurements are used to back-calculate the source level of the emission after estimating the attenuations along the path connecting the noise sources to the hydrophone. These source levels then serve as inputs for acoustic modeling, allowing for the spatial extrapolation of noise fields across the broader area of influence (Fig. 1).

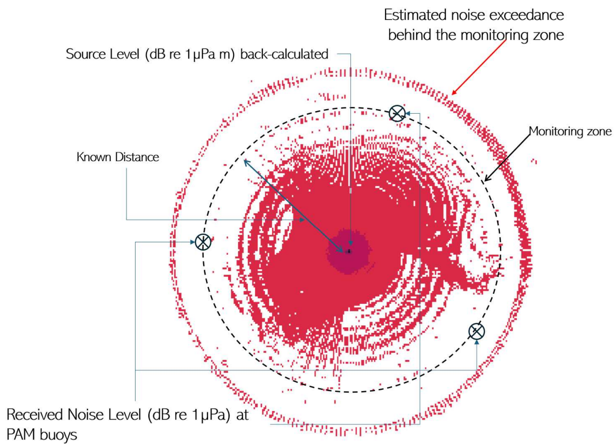

Fig. 1; Monitoring of noise resurgences behind the monitored area: in this example, red areas indicate where noise exceeds a generic impact threshold and the black dashed circle indicates the monitoring zone established at a given distance encompassing most areas of threshold exceedance. The predictive modeling allow monitoring potential exceedance of noise threshold behind the monitoring zone.

The modeling technology is currently based on solving the parabolic equation [5] using the RAM model, recognized as a benchmark for studying low-frequency noise in complex marine environments [6]. The model integrates environmental parameters such as bathymetry, sediment geoacoustic properties, wind speed, and sound velocity profiles to accurately simulate acoustic wave propagation. Simulations are performed in one-third octave bands, and the total signal sound level is obtained by summing the total sound pressures of all bands.

If the model reveals that noise thresholds are exceeded in locations where no sensors are deployed, even though the monitored points remain below threshold, the system can be configured to trigger alerts preemptively, based on modeled exceedance conditions.

Since modeling acoustic propagation in a marine environment requires advanced expertise in physical modeling and appropriate computational resources, this modeling step is presently conducted manually outside the system, requiring expert intervention to adjust thresholds and interpret results. Automating this loop (integrating real-time measurements with adaptive modeling), remains a key challenge for future development and a critical step toward more intelligent, predictive monitoring systems.

F. Data transmission and use for decision making

Communication between the acoustic buoys and the back-end server is handled via a redundant wireless strategy, combining Wi-Fi point-to-point transmission and 4G/LTE fallback. This ensures continuous data transfer even under variable environmental and connectivity conditions. Once received, data are ingested by a SpringBoot-based API and stored in a MongoDB NoSQL database. A dedicated Angular dashboard allows stakeholders—including operators, environmental officers, and decision-makers—to access real-time visualizations of underwater noise levels, marine mammal detections, and regulatory thresholds through a web interface.

The system's architecture is designed for ease of configuration, allowing changes to detection thresholds, recording intervals, or AI parameters via remotely managed JSON files. This configurability, together with its hardware-agnostic sensor layer and modular data pipeline, ensures the system can adapt across multiple operational contexts while maintaining the scientific rigor and technical reliability demanded by marine environmental regulations.

RESULTS, OPERATIONAL VALIDATION

The system underwent a comprehensive series of validation exercises to assess its performance under real-world operational and environmental conditions. These tests aimed to verify not only the technical functionality of the components: data acquisition, real-time processing, and transmission; but also the overall reliability of marine mammal detection workflows and their integration with offshore decision-making protocols.

One key stage of validation involved controlled field experiments simulating cetacean vocalizations. Acoustic signal play-back, specifically dolphin whistles and click trains, was carried out using underwater speakers (Lubell-916 cc) at various distances from the deployed buoys. The system consistently detected the simulated signals at distances ranging from 300 to 1,000 meters (Fig. 2), with minimal latency between the acoustic event and its registration on the web dashboard. These trials confirmed the sensitivity of the detection algorithms, as well as the effectiveness of the wireless communication pathways.

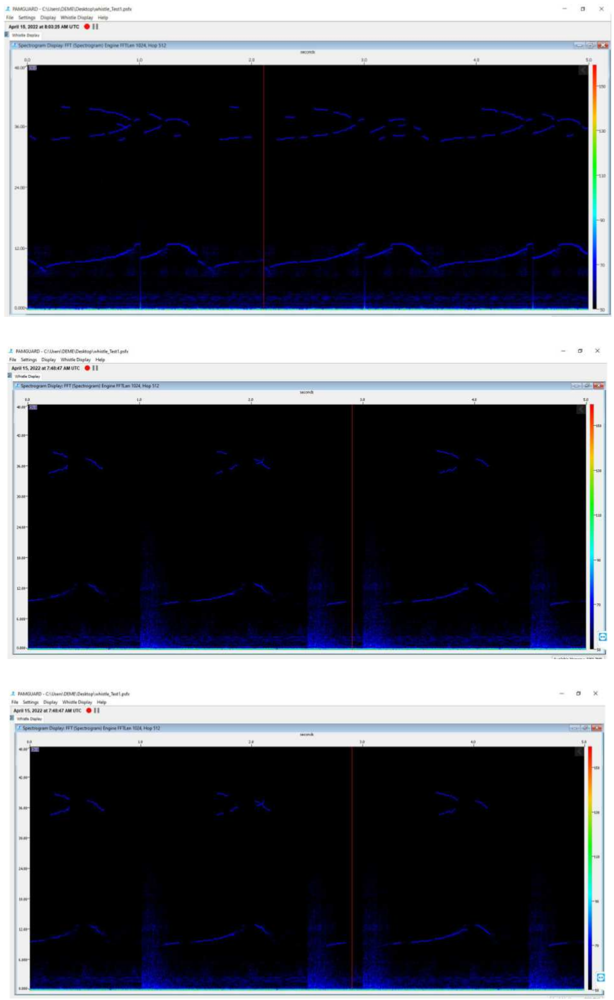

Fig. 2. Dolphin whistle (blue smoothed curves in the spectrogram) detected at 300 (top), 500 (center) and 1 000 m (bottom) from the position of the underwater speaker. (Source: Sinay)

In parallel, several full-scale deployments were carried out during offshore construction activities in France. These operational tests involved up to six acoustic buoys (Fig. 3) arranged radially around an active noise source, simultaneously.

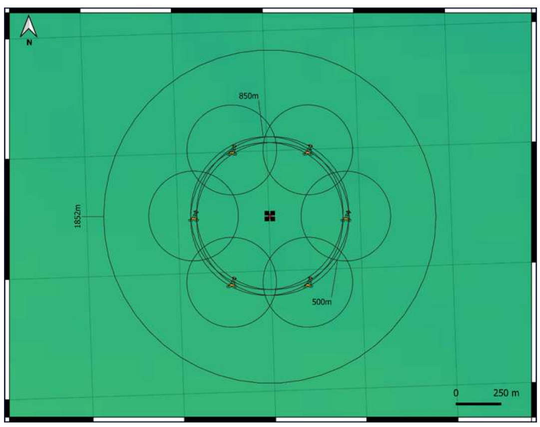

Fig. 3. Simultaneous deployment of 6 PAM buoys around an active noise

source, each at 850-m distance from the source to meet specific project requirements (Source: Sinay).

The system ran continuously over several days and demonstrated its ability to:

- Log ambient noise and calculate SEL in real time;
- Automatically trigger alerts when noise levels exceeded regulatory thresholds which depend on national specifications as well as recommendations contained in the associated EIAs ;
- Detect and classify cetacean vocalizations using onboard Sinay's AI, with further human verification through PAMGuard;
- Support Go/No-Go decisions and mitigation protocols by the environmental officer, such as delaying or interrupting pile driving when marine mammals were detected within exclusion zones.

The end-to-end system, including the AI classifiers, operator workflow, and automated reporting, proved stable and effective throughout the deployment. The data generated were used not only for compliance reporting but also for post-operational acoustic mapping and feedback to contractors and regulators. The system's performance under both controlled and industrial conditions validated its relevance for offshore monitoring missions, where mobility, responsiveness, and reliability are essential.

Furthermore, the embedded power management and ergonomic design of the buoys allowed for long-term fully autonomous operation, with minimal human intervention. This level of autonomy is crucial for offshore projects with limited access windows or constrained logistic support.

These validation efforts confirm the technological readiness of the system and its ability to bridge the gap between static scientific observatories and operational offshore monitoring needs.

Applications, Perspectives

The development of such PAM systems combining measures and predictive models for underwater noise propagation and the identification of possible ranges of impact on sensitive fauna, have direct applications in offshore and nearshore projects, including those focussed on decarbonisation and energy transition, a strategic objective in the international geopolitical context, as well as port developments and further maritime infrastructure constructions.

As an example, offshore wind farm development is a fast developing sector worldwide and entail various anthropogenic activities that act as sources of underwater noise, particularly during the installation phase (e.g., impact pile driving, vessel operations, seabed preparation) and, to a lesser extent, during the exploitation phase of the turbines. As widely acknowledged, these acoustic emissions may lead to behavioural disturbance, temporary or permanent auditory threshold shifts (TTS/PTS), or spatial displacement of marine mammals, depending on species sensitivity, received sound levels, and duration of exposure [7],[8].

Given the ecological and regulatory importance of marine mammals in offshore environments, assessing and verifying the occurrence of the impacts of underwater noise is a key requirement in project permitting and environmental compliance processes. The proposed technique presents a significant advancement by introducing a novel, field-validated system that seamlessly combines real-time acoustic monitoring, embedded AI, propagation modelling and a flexible decision-support interface. Unlike traditional systems, this approach leverages mobile, modular buoys with human-in-the-loop validation of cetacean detections and propagation modeling to extend situational awareness beyond the immediate monitoring zone. Especially, integrating propagation models appears as a crucial point. Their application in a mitigation protocol requires to compare the spatial outputs of these models against species-specific auditory thresholds and regulatory criteria such as those defined by organizations NOAA [9], ACCOBAMS [10] and ICES [11], amongst others. Since this comparison allows for the identification of the areas of potential behavioural disturbance and/or injury, the accuracy of propagation modelling is paramount for effective mitigation. The system described in this paper supports the Parabolic Equation (PE), however further models could be included in the future such as Normal Mode (NM) and Ray Tracing methods depending on the bathymetric complexity and acoustic frequency range involved [6].

Through successful field deployments and simulated trials, the framework demonstrates its ability to adapt to dynamic offshore environments, offering a scalable solution for mitigation and regulatory compliance. By bridging the gap between passive observation and proactive management, this contribution lays the foundation for a new generation of intelligent and responsive PAM technologies.

Future Developments

The increasing deployment of offshore infrastructure, including wind farms, energy exploration platforms, as well as shipping, has intensified the need for robust systems capable of real-time underwater noise monitoring and marine mammal detection. These systems are critical for assessing anthropogenic impacts, ensuring regulatory compliance and sustainability, and supporting dynamic conservation strategies. Future advancements must address integration with multi-modal sensors, scalability across diverse marine environments, and enhanced automation through data analytics and artificial intelligence.

A. Integration with Environmental and Oceanographic Sensors

One of the most promising directions for future development lies in the integration of acoustic monitoring platforms with a broader suite of environmental and oceanographic sensors.

This multi-modal approach enhances the interpretability of acoustic data by providing contextual information about the physical and biological environment. For instance, temperature and salinity profiles influence sound speed and propagation, while current velocity and turbidity affect the transmission and attenuation of acoustic signals [12], [13]. Meteorological variables such as wind speed and atmospheric pressure also modulate surface noise levels, particularly in shallow coastal regions [14]. The integration with biogeochemical sensors can help correlate acoustic activity with biological productivity, offering insights into species presence and behaviour. Also, the integration of visual and infrared imaging via surface cameras, thermal sensors, or remotely operated vehicles may add a layer of validation to acoustic detections, enabling researchers to cross-reference vocalizations with observed animal movements [15].

This sensor fusion not only improves detection accuracy but also supports adaptive monitoring strategies that respond dynamically to environmental changes, a capability increasingly vital in the context of climate-driven shifts in marine ecosystems.

B. Scalability Across Marine Environments

Scalability is essential for deploying acoustic monitoring systems across diverse marine habitats, from shallow estuaries to deep pelagic zones. Modular platforms such as moored buoys, autonomous underwater vehicles (AUVs), and gliders offer flexibility to tailor deployments to specific environmental conditions [16]. These platforms can be equipped with adaptive sensor arrays and configured for varying depths, seabed compositions, and hydrodynamic regimes.

To support real-time monitoring in remote or bandwidth-limited areas, systems must incorporate edge computing capabilities that allow for local data processing and decision-making [17]. Detection algorithms should be calibrated to local acoustic baselines, accounting for the unique mix of biological, geological, and anthropogenic sounds in each region [18]. Interoperability with existing data infrastructures, such as the European Marine Observation and Data Network (EMODnet) and the Ocean Biodiversity Information System (OBIS), may finally facilitate broader ecological assessments and ensure alignment with marine conservation policies and directives.

C. Enhanced Automation and Data Analytics

Enhanced automation and data analytics represent a key pathway to overcoming engineering constraints of PAM buoys, particularly regarding power autonomy, robustness, and compactness. Edge computing is especially promising: by processing acoustic data locally rather than transmitting or handling large uncompressed datasets, it may dramatically reduce both energy demands and bandwidth requirements [19]. Coupled with adaptive sampling and task scheduling, this approach optimizes resource use and mitigates trade-offs between buoy size, endurance, and stability.

Recent advances in machine learning further support this trend. Trained on extensive annotated datasets, machine learning models can now identify species-specific vocalizations and behavioural patterns with high precision [20]. Techniques such as transfer learning and semi-supervised training allow faster reconfiguration of detection algorithms across species and acoustic environments [21]. There is growing evidence in the literature that fully autonomous monitoring systems, capable of onboard real-time detection and reporting without immediate human oversight, are technically feasible and increasingly mature, thanks to advances in edge computing and embedded signal processing. Nonetheless, for regulatory robustness and scientific credibility, maintaining a degree of human-in-the-loop validation remains advisable.

Finally, automating acoustic propagation modeling remains a crucial frontier. Integrating adaptive models directly into the monitoring loop would extend risk assessment beyond sensor coverage, providing early warnings of potential exceedances in exclusion zones or sensitive habitats.

Together, these innovations pave the way for adaptive monitoring systems capable of dynamically adjusting parameters such as sampling rate, detection thresholds, and model updates—essential for ensuring ecological relevance and operational efficiency in complex offshore environments.

CONCLUSIONS

This work presents a novel, field-validated system for real-time underwater noise monitoring and marine mammal detection, specifically designed to meet the operational and regulatory challenges of offshore industrial activities. By combining embedded acoustic analysis, AI-driven cetacean vocalization detection, and real-time wireless data transmission, the system enables proactive management of acoustic risks in dynamic environments such as wind farm construction and other maritime noise-producing activities.

A key strength of the platform lies in its modularity and adaptability. The architecture accommodates various types of hydrophones and recorders ranging from compact integrated systems to high-sensitivity combinations, allowing tailored configurations to suit specific environmental and regulatory contexts. In addition, the inclusion of PAMGuard-based human verification workflows ensures robustness while maintaining operational responsiveness.

Field validation has demonstrated the system's solidity, autonomy, and detection reliability under both controlled and live offshore conditions. Its seamless integration into Go/No-Go decision-making procedures reinforces its role as an operational tool, rather than a post-hoc scientific instrument.

Beyond its current implementation, the system architecture offers a foundation for future enhancements, and especially dynamic acoustic modeling to estimate propagation beyond sensor coverage, and deeper integration with project-level decision support tools and dashboards. Additional work could also explore energy optimization and miniaturization to support longer-term autonomous deployments in remote or harsh environments.

In a policy landscape increasingly shaped by the Marine Strategy Framework Directive (MSFD) and international biodiversity commitments, tools that bridge regulatory compliance and technical feasibility are vital. The system described here contributes directly to this objective, offering a flexible, field-proven solution for the responsible management of underwater noise in offshore industrial operations.

ACKNOWLEDGMENT

The authors thank the engineering and scientist team of SINAY, and especially Dr. Achraf Drira for his constructive review and comments, as well as the Biodiversity & Ecosystems team of RINA Consulting.

REFERENCES

[1] C. M. Duarte *et al.*, "The soundscape of the Anthropocene ocean," *Science*, vol. 371, no. 6529, p. eaba4658, 2021, doi: 10.1126/science.aba4658.

[2] Z. Shi, N. Li, Y. Shao, N. Sun, and B. Zheng, "MCAD-MM: A benchmark dataset and method for multi-channel acoustic detection of marine mammals," *Marine Technology and Engineering*, Springer, 2025.

[3] P. Favali *et al*. (2013). NEMO-SN1 Abyssal Cabled Observatory in the Western Ionian Sea. *IEEE Journal of Oceanic Engineering*, vol. 38, no. 2, pp. 358-374, April 2013, doi: 10.1109/JOE.2012.2224536

[4] Hachicha Belghith, E., Rioult, F., Bouzidi, M. (2020). Acoustic Diversity Classification using Machine Learning Techniques: Towards Automated Marine Big Data Analysis. *International Journal on Artificial Intelligence Tools*. DOI: 10.1142/S0218213020600118

[5] Collins, M. D. (1993). A split-step Pad{é} solution for the parabolic equation method. *The Journal of the Acoustical Society of America*, 93(4), 1736–1742.

[6] Farcas, A., Thompson, P. M., & Merchant, N. D. (2016). Underwater noise modelling for environmental impact assessment. *Environmental Impact Assessment Review*, 57, 114–122. https://doi.org/10.1016/j.eiar.2015.11.012

[7] Southall, B.L., Bowles, A.E., Ellison, W.T., Finneran, J.J., Gentry, R.L., Greene Jr., C.R., ... Tyack, P.L. (2007). Marine mammal noise exposure criteria: Initial scientific recommendations. *Aquatic Mammals*, **33**(4), 411–521..

[8] Erbe, C., Marley, S.A., Schoeman, R.P., Smith, J.N., Trigg, L.E., Parsons, M.J.G. (2019). The effects of ship noise on marine mammals—A review. *Frontiers in Marine Science*, **6**, 606.

[9] NMFS (National Marine Fisheries Service). (2018). *Technical Guidance for Assessing the Effects of Anthropogenic Sound on Marine Mammal Hearing* (Version 2.0). U.S. Department of Commerce, NOAA.

[10] ACCOBAMS. (2021). Guidelines for underwater noise mitigation measures. Agreement on the Conservation of Cetaceans in the Black Sea, Mediterranean Sea and contiguous Atlantic area.

[11] ICES. (2022). *Working Group on Marine Mammal Ecology (WGMME) Report 2022*. ICES Scientific Reports 4:41.

[12] Urick, R. J. (1983). *Principles of underwater sound*. McGraw-Hill.

[13] Medwin, H., & Clay, C. S. (1998). *Fundamentals of acoustical oceanography*. Academic Press.

[14] Wenz, G. M. (1962). Acoustic ambient noise in the ocean: Spectra and sources. *Journal of the Acoustical Society of America*, *34*(12), 1936–1956.

[15] Chabot, D., & Bird, D. M. (2015). Wildlife research and management methods in the 21st century: Where do unmanned aircraft fit in? *Journal of Unmanned Vehicle Systems*, *3*(4), 137–155.

[16] Moline, M. A., Blackwell, S. M., von Alt, C., Allen, B., Austin, T., Case, J., … & Stokey, R. (2005). Remote Environmental Monitoring Units: An Autonomous Vehicle for Characterizing Coastal Environments. Journal of atmospheric and oceanic technology, *22*(11), 1797–1808.

[17] Delory, E., & Pearlman, J. (2018). Challenges and Innovations in Ocean In Situ Sensors. https://doi.org/10.1016/C2015-0-06798-3. Elsevier.

[18] Van Parijs, S. M., Clark, C. W., Sousa-Lima, R. S., Parks, S. E., Rankin, S., Risch, D., & Van Opzeeland, I. (2009). Management and research applications of real-time and archival passive acoustic sensors over varying temporal and spatial scales. *Marine Ecology Progress Series*, *395*, 21–36.

[19] Heidemann, R. M. (2020). *Underwater acoustic telemetry with edge computing for low-power embedded systems* (Doctoral dissertation). Virginia Polytechnic Institute and State University, Blacksburg, VA.

[20] Frasier K. E. (2021) A machine learning pipeline for classification of cetacean echolocation clicks in large underwater acoustic datasets. PLoS Comput Biol 17(12): e1009613. https://doi.org/10.1371/journal.pcbi.1009613

[21] Shiu, Y., Palmer, K. J., Roch, M. A., Fleishman, E., Liu, X., Nosal, E. M., … & Helble, T. A. (2020). Deep neural networks for automated detection of marine mammal species. *Scientific Reports*, *10*, 607.