A Survey of Deep/Machine Learning in Maritime Communications

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***Abstract*— In recent years Machine learning has begun to show its potential in all domains of life, including the field of maritime communications. Research on and attempts to use Machine learning in maritime communications have been conducted in recent years. Some of the major research areas of Machine Learning driven maritime communications are channel selection, channel coding, synchronization, and positioning system. To this purpose, the incorporation of ML into maritime communications adds a dimension to wireless connectivity that surpasses current deployments, which mostly rely on satellite links with significant latency and shore-based base stations with limited coverage.**

Keywords—Maritime communications, Machine learning, Channel selection, Synchronization and Positioning system.

I. Introduction

The numerous issues, developments, and predictions related to machine learning in maritime communications are covered in this study. Numerous unique technologies have been made possible by recent developments in ML research. More substantial developments will be needed because of the growing demand for connectivity in the maritime environment. [1]

Underwater computing has drastically changed over the years. [2] Applications that rely on remotely or autonomously controlled vehicles and offline analysis of material gathered during specialized underwater activities have become more prevalent in recent years. The automatic analysis of the data gathered using these methods can be supported by ML. [3] Along with enabling various monitoring applications, ML can also be utilized to improve the performance of AUVs, ROVs, and other infrastructure, including buoys with integrated computing and seabed sensor networks. [4] Here, we provide a quick overview and analysis of the ML in oceans' present application domains.

This present paper is as follows in section 2 we describe the areas where machine learning can be incorporated into maritime communications. In section 3 we concluded the contribution of this paper. Figure 1 describes the communication architecture of maritime communications.

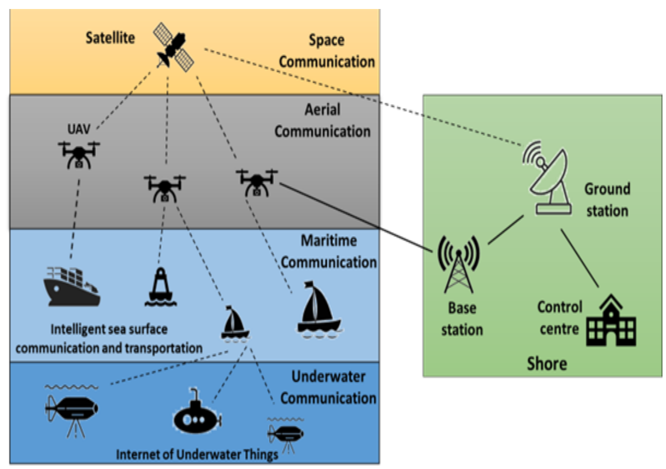

Fig 1. An illustrative showing of the maritime communication architecture.

II. Machine Learning Research areas in Maritime Communications

Channel selection, Synchronization, and Positioning system are some of the main research areas of ML-driven maritime communications. This section discusses technical developments and future potential in these areas.

A. Channel Selection

Channel selection is important in many communication protocols since it tells us how the channel transmits and distorts the signal. The conventional method can make it challenging to deduce in challenging channel conditions. However, deep learning-based channel selection can simplify the task despite the challenging channel characteristics in the maritime environment.

The main concern of Hoeft et al. [5] is the issue of selecting the best communication link from a range of alternatives presented by a heterogeneous communication environment with multiple communication technologies available to vessels using shipping lanes or waiting at port approaches and thus having access to onshore communication infrastructure. Deep Learning Regression Link Evaluation Method (DLR-LEM) and Simultaneous Deep Learning Link Evaluation Method are the two supervised learning solutions they proposed (SDL-LEM).

A software-defined marine communication network framework called S-DQN is presented by Yang et al. [6] to address the issue of high temporal complexity and the curse of dimensionality in data transfer. Comparatively speaking, the suggested algorithm ensures reliability while enhancing the quality of sent data.

This study [7] found the complexity and instability of underwater acoustic communication systems. They then presented a boosted regression tree technique on their own dataset, subject to SNR and BER, and evaluated the correctness of the results.

In order to address the problem of managing joint computation and communication resources in an integrated maritime network that connects space, air, ground, and sea, Xu et al. [8] introduced a deep reinforcement-based learning approach that focuses on reducing resource utilization and computation task execution delays.

It is currently more practical to keep using deep learning approaches to develop, improve, and optimize the channel selection process for marine communications given the complexity of the process.

We can utilize supervised, unsupervised, and reinforcement learning techniques to enhance channel selection in marine communications. These approaches can be complemented by incorporating expert knowledge and domain expertise. These strategies' effectiveness is influenced by the data's quality, the communication scenario's complexity, and the deployment environment.

TABLE I. DESCRIBES THE SUMMARY AND CONTRIBUTIONS OF CHANNEL SELECTION IN MARITIME COMMUNICATIONS.

Reference	Summary	Contributions
[5] Hoeft et al.	The article introduces the idea of using deep neural networks to choose the appropriate links.	I. A summary of handover procedures and significant features of maritime wireless access systems that are crucial for creating accurate models of the communication environment. II. To perform link assessment in the marine environment, the utilization of deep learning techniques can significantly decrease the measurement traffic needed. III. An assessment of the suggested approaches in contrast to other frequently used methods.
[6] Yang et al.	A new approach to schedule transmissions using an improved deep Q-learning algorithm. This technique merges the deep Q-network with softmax multiple classifiers, commonly referred to as the S-DQN algorithm, while also defining the optimization objectives, such as delay, cost, and energy.	I. The framework incorporates the deployment of network infrastructure across space, air, earth, and sea to enable the joint transmission of data forwarding, resulting in enhanced transmission efficiency. II. The simulation outcomes utilizing various system parameters confirm the efficacy of the suggested approach. In comparison to conventional methods, this scheme markedly enhances the transmitted data's quality while ensuring the dependability and promptness of maritime communication.
[7] Alamgir et al.	The goal of this research is to evaluate a sea trial dataset and identify the best link adaptation approach based on channel quality. A rule-based approach, including 3D and modulation-wise analyses and a fixed-SNR strategy, is employed. A graph of UAC network data rate vs. SNR/BERT is used to determine the optimal AMC combinations for adapting to changes in the channel.	I. This article tackles the aforementioned challenges by utilizing machine learning (ML) techniques to classify modulation and coding scheme (MCS) levels. II. The objective of this study is to create a link-adaptation system capable of improving spectral efficiency in all channel conditions while maintaining the required level of covertness and reliability. III. The sea trial datasets they measured illustrate that the channel undergoes significant variations over time, including changes from morning to noon, day to night, and summer to winter.
[8] Xu et al.	This study presents a network architecture that integrates space, air, ground, and sea components with edge and cloud computing features. The architecture aims to deliver adaptable hybrid computing services for maritime operations.	I. Within the integrated network, edge computing services and network access are made available to users using satellites and unmanned aerial vehicles (UAVs). II. Using the architecture as a foundation, the problem of allocating communication and computation resources is formulated as a complex decision process. A solution to this intricate optimization problem is then developed using

		deep reinforcement learning techniques.

B. Synchronization

In general, cell synchronization processes are required for all wireless devices. In order to meet the requirements of the maritime environment, even in the poorest radio channel environment or quickest communication, it is crucial to have synchronization technology.

In this study [9], two competing neural networks—an evaluated neural network, which chooses the power control policy, and a target neural network, which modifies the weights of the networks to compute long-term discounted utility and thus lessens the overestimation error—are used for the transmitting ship and the UAV.

They presented a novel routing scheme in this study [10] with the goal of directly addressing the various underwater world variability types. Channel-aware Reinforcement learning-based Multi-path Adaptive Routing is the name of their protocol. In order to dynamically adapt the size of the set of relays to the current channel circumstances, they carefully constructed CARMA. When the network conditions are good, CARMA automatically shifts between quick and energy-efficient single-path routing and more reliable multi-path routing (unfavourable forwarding).

MCN [11] has the ability to offer global coverage and varied Quality-of-Service (QoS) provisioning through the incorporation of contemporary information network technology and the coupling of space, air, ground, and marine network segments. When connected via Sixth Generation (6G) mobile networks, this integration of network segments includes processing, caching, sensing, and control capabilities in addition to conventional communication services.

To achieve global optimal performance with the possibility of implementation of the end-to-end deep neural network including synchronization-based communication system can be built. We can utilize cutting-edge techniques support vector machines to precisely predict synchronization issues and modify the timing of messages in order to optimize the synchronization process for wireless devices in marine communications. Additionally, the use of reinforcement learning algorithms can enable wireless devices to learn from their environment and make better synchronization decisions in dynamic and noisy conditions.

TABLE II. DESCRIBES THE SUMMARY AND CONTRIBUTIONS OF SYNCHRONIZATION TECHNOLOGY IN MARITIME COMMUNICATIONS.

Reference	Summary	Contributions
[9] Liu et al.	This system allows for the independent selection of power control policies by the transmitting ship and the UAV, without requiring information about the jamming or message generation models.	I. One network is responsible for selecting the power control policy, while the other network updates its weights. II. The duelling architecture utilizes two streams to estimate the current state's value and the state-dependent advantage function of the power control policy.
[10] Di et al.	This proposal involves a novel data forwarding scheme that enables rapid adaptation of relay selection to change conditions in the underwater channel.	I. The performance of CARMA was compared to three other routing solutions, namely CARP, QELAR, and EFlood, using both SUNSET-based simulations and sea-based experiments. II. The results demonstrate that CARMA outperforms all other protocols with respect to packet delivery ratio, achieving up to 40% higher delivery rates. Additionally, CARMA delivers packets faster than CARP, QELAR, and EFlood, while maintaining lower network energy consumption.
[11] Khan et al.	A resource-efficient authentication mechanism has been proposed for an integrated MCN that encompasses space, air, ground, and sea networks.	I. ECC was utilized to achieve an equivalent level of security with a smaller key size. II. Additionally, comparisons with similar schemes are included. III. The proposed scheme offers an improved tradeoff between security and efficiency.

C. Positioning System

Current maritime positioning system technology has been determined using a mathematical technique based on a variety of wireless channels and mobile devices, which can result in considerable positional mistakes. The implementation of deep learning models is what distinguishes deep learning technology as it is now being used in location technology.

It is obvious that signal and data processing approaches affect the estimation accuracy of localization systems. Therefore, excellent localization accuracy is supported by recent developments in machine learning, data processing, and analysis. This study aims to examine the development of wireless localization standards and methodologies over the past two decades, as well as how they have affected localization accuracy. The study provides a narrative on the new directions in localization technology, both geometric and non-geometric. [12]

This study [13] constructed a simulation dataset based on a realistic French river because there isn't a dataset that matches the different types of inland conditions. They employed the ConvLSTM technique, a reliable and effective deep learning model, to give precise ship mobility prediction. We use the federated learning approach to carry out collaborative learning among ships without jeopardizing their privacy.

To forecast spatiotemporal vessel trajectories, a flexible and powerful AIS data-driven deep learning system that incorporates the social force notion into the original LSTM network is developed. The suggested SFM-LSTM has demonstrated accurate and reliable prediction performance when tested on realistic vessel trajectories in various sea environments. To make SFM-LSTM more dependable and robust in varied navigation situations, a mixed loss function is provided that measures both offset distance and direction between the true and predicted timestamped sites. [14]

According to various 6G network architectures, they can enable marine surveillance and search and rescue operations, give dynamic resource provisioning in terms of radio access, caching, and computation, and minimize the effects of regional factors on route loss. They can also shorten communication delays, increase communication dependability through extra wireless channels, and provide reduced communication delays. [15]

Machine learning can improve the positioning system in maritime communications by developing predictive models, recognizing patterns, analysing data in real-time, and improving accuracy. This can enhance safety, optimize navigation routes, and improve the accuracy of location data.

TABLE III. DESCRIBES THE SUMMARY AND CONTRIBUTIONS OF THE POSITIONING SYSTEM IN MARITIME COMMUNICATIONS.

Reference	Summary	Contributions
[12] Zekavat et al.	Positioning technologies such as the Global Positioning System (GPS), indoor localization using WiFi, cell-phone-based localization (which involves the fusion of GPS, cell-tower-based localization, and dead-reckoning), and inertial/dead-reckoning techniques are commonly used.	I. History of localization. II. The primary technological advancements that enable localization. III. Future direction
[13] Hammedi et al.	The paper introduces a new collision detection system for inland ships that utilize Federated Deep Learning to create a reliable positioning prediction model.	I. Collaborative learning among ships. II. To ensure real-time response and prevent ship collisions, a safety system is implemented at the Multi-access Edge Computing (MEC) nodes, which facilitates low-latency communication
[14] Liu et al.	This study suggests a data-driven approach for trajectory prediction using AIS data, utilizing the powerful learning capability of deep neural networks. The proposed framework primarily employs a Long Short-Term Memory (LSTM) network as its key component.	I. High-accuracy trajectory positioning. II. Realistic AIS-based vessel trajectories.
[15] N. Nomikos et al.	The authors of this paper performed a systematic literature review (SLR) to investigate previous studies on age minimization in UAV-assisted data-gathering architecture. The objective of the review was to identify the critical design components involved in age minimization.	I. Energy management, flight trajectory, and UAV/SN scheduling. II. In addition to the current challenges, there are also future considerations that need to be addressed, such as traffic prioritization, packet delivery errors, system optimization, association between UAVs and sensor nodes, and physical impairments.

III. CONCLUSION

The fast pace of research in the field of ML may enable every maritime communication medium to possess some sort of intelligence that can be used positively. This survey has discussed machine/deep learning use in maritime network topologies, where they provide a wide range of marine IoT and broadband service use cases. The article also demonstrates how edge computing, big data analytics, and the Internet of Things (IoT) can be combined to further improve the capabilities of these systems. Despite the numerous opportunities these technologies offer, their effective application is dependent on a number of elements, such as data accessibility, system complexity, and regulatory compliance. To address these issues and realize the full potential of deep/machine learning in maritime communications, more research and development activities are required.

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