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Deep Learning-Based Beam Selection in RIS-Aided Maritime Next-Generation Networks with Application in Autonomous Vessel Mooring

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Abstract: Maritime communication networks are critical for supporting the increasing demands of oceanic and coastal activities, including shipping, fishing, and offshore operations. However, traditional systems face significant challenges in providing reliable, high-throughput connectivity due to dynamic sea environments, mobility, and non-line-of-sight (NLoS) conditions. Reconfigurable intelligent surfaces (RISs) have been proposed as a promising solution to overcome these limitations by enabling programmable control of electromagnetic wave propagation in next-generation mobile communication networks, such as beyond fifth generation and sixth generation ones (B5G/6G). This paper presents a deep learning-based (DL) scheme for beam selection in RIS-aided maritime next-generation networks. The proposed approach leverages deep learning to optimize beam selection dynamically, enhancing signal quality, coverage, and network efficiency in complex maritime environments. By integrating RIS configurations with data-driven insights, the proposed framework adapts to changing channel conditions and potential vessel mobility while minimizing latency and computational overhead. Simulation results demonstrate significant improvements in both machine learning (ML) metrics, such as beam selection accuracy, and overall communication reliability compared to traditional methods. More specifically, the proposed scheme reaches around 99% Top-K Accuracy levels while jointly improving energy efficiency (ee) and spectral efficiency (SE) by approx. 2 times compared to state-of-the-art approaches. This study provides a robust foundation for employing DL in RIS-aided maritime networks, contributing to the advancement of intelligent, high-performance wireless communication systems for advanced maritime applications, such as autonomous mooring, the autonomous approach, and just-in-time arrival (JIT).

Keywords: machine learning; deep learning; maritime communications; B5G; sixth-generation communication networks; beam selection; radio resource management; autonomous mooring; smart port

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1. Introduction

Maritime communication networks are pivotal for ensuring safety, efficiency, and seamless connectivity across oceanic and coastal regions. With the rapid expansion of maritime industries such as intelligent transportation and offshore energy production, there is an increasing demand for high-capacity, reliable, and low-latency wireless communication systems [1]. Traditional maritime communication systems rely heavily on line-of-sight (LoS)

links and struggle to meet the aforementioned requirements due to the harsh propagation environments, dynamic sea surfaces, and limited infrastructure [2].

Modern mobile communication systems, particularly those envisioned for beyond fifth generation (b5g) and sixth generation (6G), aim to provide ubiquitous connectivity with ultra-high throughput, massive device service provisioning, and enhanced energy efficiency (EE). It is already visible that these networks can act as integrators for diverse service categories and moder-era applications due to their ability to efficiently serve diverse user requirements while maintaining the needed quality of service (qos) and quality of experience (QoE) levels [3,4]. From a physical layer standpoint, the aforementioned tradeoff between the enhanced requirements and the guaranteed levels of performance metrics involves the introduction of several novel technologies such as millimeter-wave (mmWave) transmission, non-orthogonal multiple access (NOMA), massive multiple-input multiple-output orientations (mMIMOs), physical layer security (PLS), and reconfigurable intelligent surfaces (RISs) [4,5]. This manuscript focuses on the advent of RISs, which offer transformative potential for next-generation maritime networks. RIS technology introduces programmable surfaces capable of dynamically manipulating electromagnetic waves, enabling the enhancement of signal strength and a reduction in interference and overcoming non-line-of-sight (NLoS) challenges [6]. When integrated with beamforming techniques, RIS provides a highly adaptable framework for optimizing wireless communications in challenging maritime scenarios [7,8].

In the evolving landscape of maritime B5G/6G networks, artificial intelligence (AI) and machine learning (ML) have become indispensable tools for gaining actionable insights from the high-volume and heterogeneous data that are constantly and continuously generated by the users of those networks. These technologies are crucial for enabling intelligent decision-making, automating diverse service requirements, and managing radio resources efficiently [9]. The extensive data (big data) produced in dynamically evolving and densely populated B5G/6G environments serve as a foundation in the training process of various learning algorithms. However, deriving meaningful insights and adjusting critical parameters requires substantial computational resources to train and execute AI/ML models effectively. Consequently, accelerating the training process and minimizing inference times are vital for ensuring the practicality, applicability, and overall efficiency of AI/ML-driven solutions within next-generation (NG) networks [10,11]. By employing deep learning-based approaches, beam selection in RIS-aided networks can be optimized to enhance both performance and adaptability. Nevertheless, applying deep learning in RIS-aided maritime scenarios presents unique challenges due to the dynamic maritime environment, vessel mobility, and stringent resource constraints [12–16].

Contributions and This Paper's Structure

Considering the above, this paper explores a deep-learning-based approach for beam selection in RIS-aided maritime networks, aiming to enhance throughput, reduce latency, and ensure reliable connectivity. Specifically, the proposed framework addresses the interplay between RIS configurations and beamforming strategies while adapting to the unique characteristics of maritime environments. Through extensive evaluation rounds, the proposed approach demonstrates the effectiveness of this methodology in overcoming challenges associated with beam selection in RIS-aided maritime next-generation networks. As DL and RIS constitute an emerging field in the maritime domain, this paper also explores several open challenges and research directions, aiming to stimulate further interest and advancements in 6G-enabled maritime services. The key contributions of this article are as follows:

- The motivation behind using RIS and DL in maritime environments and differences with applying these in other B5G/6G killer application domains are discussed.
- The application of RIS techniques in maritime communication and relevant applications is discussed together with the current state of the art in conventional ML- and DL-aided solutions.
- An illustrative use case aimed at the optimization of beam selection using DL principles using a maritime-driven dataset generated via extensive simulation rounds is presented, highlighting the performance of the model based on both ML metrics (e.g., high accuracy levels) and network ones (e.g., throughput level maximization).
- Open issues are discussed in order to stimulate further research in DL-assisted B5G/6G maritime environments.

The rest of this paper is organized as follows: In Section 2, RIS and ML for B5G network orientations are presented, highlighting the need for such technologies in modern-era maritime environments. In Section 3, the different maritime use cases where these technologies can be implemented are depicted. Section 4 presents the proposed DL-based beam selection framework for RIS-aided B5G maritime applications based on energy efficiency (EE) level optimization. Moreover, the overall simulation set-up and parameters are presented along with the simulation results. In Section 5, the known issues for the effective application of the proposed technologies in challenging maritime environments are depicted. Finally, concluding remarks are outlined in Section 6.

2. Reconfigurable Intelligent Surfaces and Deep Learning

The integration of RISs and Deep Learning (DL) marks a significant milestone for advancing wireless communication, particularly for B5G networks. As maritime scenarios constitute one of the major verticals in B5G/6G use case scenarios, these technologies are proposed as an efficient manner to deal with the increasing needs of maritime users and the complex high-interfering maritime over-the-air and over-sea communication channels. This section explores the fundamental technologies involved and their synergistic application in addressing the unique challenges of these challenging topologies.

2.1. Description of the Technologies

RISs are engineered electromagnetic (EM) surfaces with programmable physical properties designed to intelligently reshape the wireless propagation environment. By altering the behavior of incident radio waves, RISs can direct signals to desired receivers to enhance their power or mitigate interference at unintended receivers [17]. These surfaces consist of numerous low-cost, low-power scattering elements capable of adjusting both the amplitude and/or phase of impinging signals, serving primarily as supportive, passive components in communication systems. Passive RIS technology requires minimal energy, as power is only needed for reconfigurability. For more advanced capabilities, active RISs integrate power amplifiers in selected elements to further refine signal adjustments [18,19]. The hybrid RIS concept has also emerged recently, combining passive and active elements to optimize performance [20]. Unlike other key enabling technologies for B5G and 6G networks, such as relay nodes, massive MIMO, ultra-dense networks, and millimeter-wave communications, RISs offer a cost-effective approach for key performance indicator (KPI) enhancement (such as network coverage, spectral efficiency, throughput, and EE,) in next-generation wireless systems, particularly in scenarios with deep fading or NLoS conditions where direct signal paths are inadequate. Moreover, RISs eliminate the need for power amplifiers, RF chains, and complex encoding/decoding algorithms, which significantly reduces costs and complexity [19,20].

RIS can be seamlessly integrated into existing wireless networks by being mounted on different locations such as building facades, walls, ceilings, roadside billboards, clothing, or even vehicles, offering exceptional flexibility. These attributes make RIS a transformative technology for addressing the growing demands of future wireless communication systems [21].

RIS operation principles are based on the interplay of metasurface physics and advanced signal processing. Mathematically, the behavior of RIS in a mMIMO B5G topology can be described as follows. Given a transmitter equipped with M antennas communicating with a single user through an RIS with N passive reflecting antenna elements, the received signal y can be expressed as

$$y = h_d x + h_r^H \Phi H_t x + n \tag{1}$$

where

- y is the received signal vector;
- x is the transmitted signal vector from the base station;
- $h_d \in \mathbb{C}^{1\times M}$ is the direct channel vector from the base station to the user;
- $H_t \in \mathbb{C}^{N\times M}$ is the channel matrix from the base station to the RIS;
- $h_r \in \mathbb{C}^{N\times 1}$ is the channel vector from the RIS to the user;
- $\Phi = diag(e^{j\varphi_1}, e^{j\varphi_2}, \ldots, e^{j\varphi_N})$ is the diagonal phase-shifting matrix of the RIS, where φ_N represents the phase shift applied by the n-th element;
- n is the additive white Gaussian noise (AWGN) vector with zero mean and variance σ^2.

The total effective channel gain can be expressed as

$$h_{eff} = h_d + h_r \Phi H_t \tag{2}$$

The received signal power can then be maximized by jointly optimizing Φ and x. The optimal phase shifts in the RIS elements are determined to align the reflected signal's phase with the direct path for constructive interference:

$$\varphi_n^* = -\arg(h_{r,n}^H H_{t,n}) \tag{3}$$

where $h_{r,n}$ and $H_{t,n}$ represent the n-th element's contributions in the RIS–user and RIS–base station channels, respectively.

For mMIMO systems, the beamforming vector w_m for the m-th antenna at the base station can further enhance the system's performance. Then, the transmitted signal is given by

$$x = \sum_{m=1}^{M} w_m s_m \tag{4}$$

where s_m is the data symbol for the m-th user. Joint optimization of beamforming (w_m) and RIS phase shifts (Φ) is crucial for maximizing spectral efficiency.

The total system's achievable rate for the user is given by

$$R = \log_2(1 + \frac{\left\| h_{eff} x \right\|^2}{\sigma^2}) \tag{5}$$

Deep learning (DL), a subset of machine learning, utilizes artificial neural networks with multiple layers to extract complex patterns from data. It plays a crucial role in tasks such as image recognition, natural language processing, and, more recently, wireless communication. By analyzing vast datasets, DL models can predict channel states, optimize resource allocation, and adapt to dynamic network conditions in real time [4].

The application of ML/DL methods to optimize the utilization of RIS in wireless networks represents an emerging and innovative approach, as explored in various recent studies. These studies have addressed topics such as symbol estimation, cooperative communications, indoor signal focusing, and secure wireless communications. Results obtained using deep learning techniques frequently outperform, or at least match, those of conventional methods while significantly reducing computational complexity [21–23].

The synergy between RIS and DL lies in their complementary capabilities. While RIS provides the physical mechanism to reconfigure the wireless environment, DL offers the computational intelligence to dynamically predict and optimize system performance. This combination is particularly potent in addressing the complexities of maritime communication, where environmental factors such as oceanic wave interference, the mobility of vessels, and sparse infrastructure present unique challenges.

2.2. The Need for RIS-Aided Communication in B5G Maritime Orientations

Maritime communication networks have traditionally lagged behind terrestrial networks due to their unique operational challenges. The vast and dynamic nature of ocean environments, combined with limited infrastructure, makes achieving reliable and high-speed communication a daunting task. As maritime industries adopt more data-intensive applications, including autonomous shipping, just-in-time arrival (JIT), remote monitoring, and Internet of Things (IoT) devices, the need for robust communication networks becomes critical.

RIS-aided communication offers a compelling solution for B5G maritime networks. By deploying RIS on vessels, buoys, or offshore platforms, it becomes possible to create adaptive and efficient communication channels. These surfaces can mitigate signal degradation caused by environmental factors such as water vapor, surface reflections, and moving obstacles. Furthermore, RIS can create virtual LoS paths in NLoS conditions, enhancing connectivity in challenging environments [24].

Moreover, the energy efficiency of RIS aligns well with the operational constraints of maritime applications, where access to power sources is often limited. By leveraging their passive or low-power nature, RIS can facilitate sustainable communication solutions for remote maritime operations [25].

Deep learning further enhances the potential of RIS in maritime settings. DL algorithms can analyze the complex propagation environment of the sea, predicting optimal configurations for RIS in real time. For instance, DL models can determine the best beamforming patterns or signal paths, ensuring seamless connectivity even under highly dynamic conditions. Additionally, DL can assist in proactive network management by identifying potential disruptions and adapting network parameters to maintain performance.

As maritime communication evolves to support autonomous vessels, advanced logistics, and real-time monitoring, the role of RIS and DL becomes indispensable. Together, they enable high-capacity, reliable, and adaptive communication networks that can meet the stringent demands of the B5G era and beyond.

In order to further explain all the above, Figure 1 depicts RIS operations in different B5G maritime scenarios, where DL techniques are also utilized.

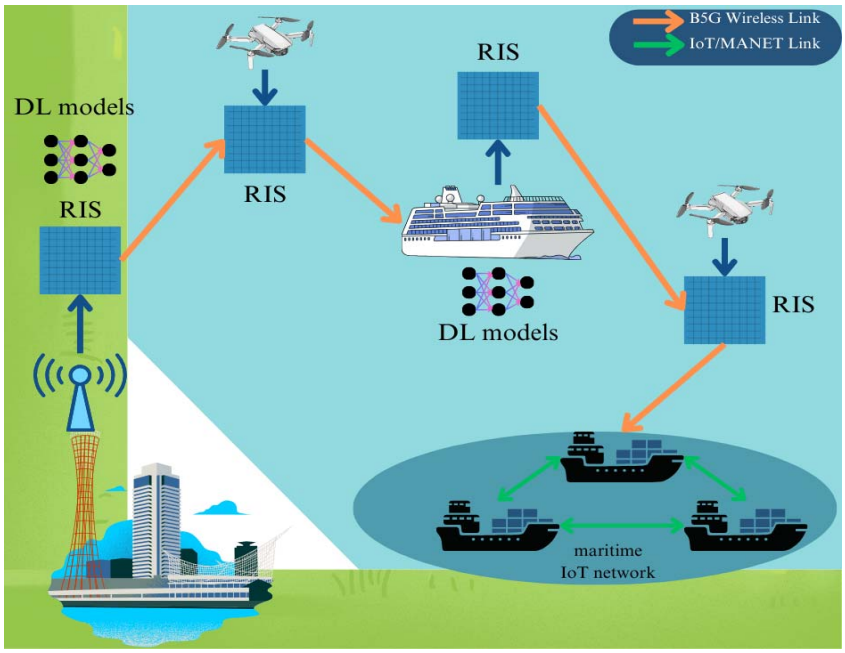


Figure 1. DL-based and RIS-assisted B5G communications in maritime scenarios, including land-to-ship, ship-to-ship, and maritime IoT/MANET.

3. Maritime RIS Use Cases

This section discusses RIS-aided maritime communication solutions in various land-to-sea, over-sea, and underwater use cases in the context of 5B/B5G networks. Moreover, the major challenges in RIS deployment in such scenarios are depicted. Table 1 summarizes these solutions and highlights their main points.

Table 1. RIS-aided techniques for maritime applications.

Work	Maritime Application	Method	Open Issues
[25]	Port-to-Ship communications	UxV (Drone and/or underwater) RISs in INTENT networks to reduce energy consumption and increase SE	Maritime channel complexity, implementation cost, hardware impairments, and real-scenario testing
[26]	Port-to-Ship communications	Optimal RIS reflection element selection for blocked offshore users via achievable rate maximization	Implementation cost, need for a large number of reflecting elements to achieve rate maximization
[27]	Security and Privacy	UAVs secure sensor data collection and data upload scheduling schemes to minimize AoI	UAV trajectory prediction, maritime channel estimation and characterization, and secrecy rate maximization
[28]	Security and Privacy	The DRL framework to maximize EE and QoS in extensive jamming UAVs and RIS-aided maritime environments	Practical difficulties in mounting RISs into UAVs, increased power consumption in large-scale systems, and wind-induced movement
[29]	Underwater communications	Outage probability performance evaluation in air-to-underwater RIS scenarios	Salty water, air bubble presence, and temperature seriously affect the overall system's performance

3.1. Port-to-Ship Communications

Port-to-ship communication represents one of the most critical use cases for RIS-aided maritime networks, addressing the increasing demand for high-throughput and reliable connectivity during docking and departure operations. Traditional systems often suffer from severe signal degradation due to obstructions, such as cranes, storage facilities, and large vessels, as well as dynamic environmental factors like sea waves and atmospheric

interference. The deployment of RISs, particularly in unmanned aerial vehicles (UAVs) or mounted on port infrastructure, has emerged as a viable countermeasure to overcome these challenges, as also depicted in Figure 2.

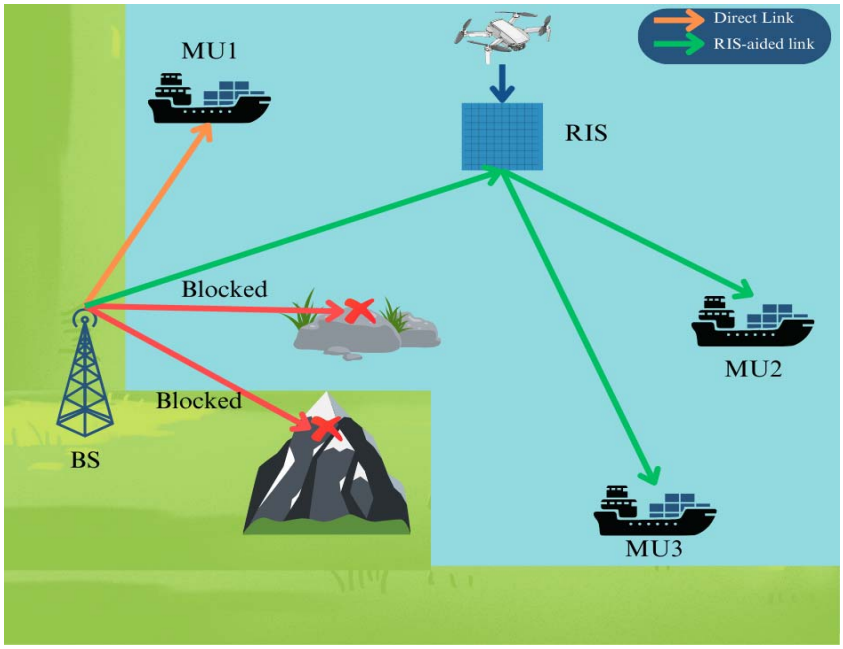


Figure 2. RIS-assisted B5G communications in port-to ship communication scenarios, including BS deployed in land and maritime users (MUs) deployed in sea.

In this framework, the authors in [25] proposed a novel RIS-aided NOMA scheme to increase the overall system's capacity and spectral efficiency (SE) and reduce energy consumption in unmanned vehicle (UxV) maritime scenarios. Similarly, in [26], a channel estimation and optimal beam selection scheme is proposed in similar topologies by considering aerial RISs for blocked offshore users.

In the aforementioned works, advanced methods, such as the optimal selection of RIS reflection elements, have been proposed to mitigate issues faced by blocked offshore users [25]. In these cases, authors in [26] confirmed that the higher the number of the base station's (BS) and RIS antenna elements, the better the capacity and the signal-to-noise-plus-interference ratio (SNIR). Moreover, channel characterization and estimation are easier due to the increased number of channel observations [26]. However, practical implementation in real-world maritime environments poses significant challenges, including high deployment costs, hardware impairments, and the complexity of maritime channel environments [25,26]. Furthermore, ensuring energy efficiency in these systems remains a key concern, especially when operating UAV-mounted RISs that rely on limited power sources [26]. As port-to-ship communication systems evolve, integrating RIS with deep learning-based algorithms for real-time beamforming optimization could further enhance spectral efficiency and reliability, meeting the growing data demands of modern port operations.

3.2. Security and Privacy

The integration of RISs into maritime networks introduces new possibilities for enhancing security and privacy in communication systems. Secure data transmission is particularly crucial in maritime environments, where sensitive information, such as ship manifests, real-time navigation data, and IoT sensor readings, must be protected from unauthorized access or malicious interference. RISs, when combined with UAVs, offer a

unique approach for ensuring secure communication by dynamically shaping the signal paths and mitigating potential eavesdropping or jamming attempts, as depicted in Figure 3.

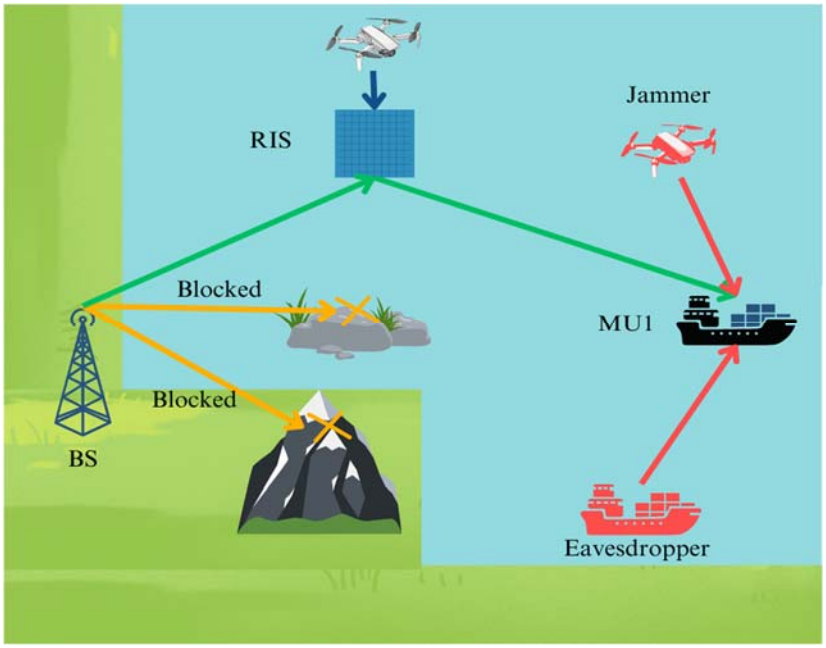


Figure 3. RIS-assisted B5G communications under eavesdropping and/or jamming attempts in the maritime domain.

In this context, the authors in [27] introduce an Age-of-Information (AoI)-driven secure transmission strategy for maritime wireless sensor networks. Their approach facilitates secure data transmission to an onshore base station (BS) with the assistance of UAVs and RIS, even in the presence of nearby eavesdroppers. The proposed strategy divides secure transmission into two sequential phases: data collection and data upload, aiming to minimize the AoI of private information. During the data collection phase, two scheduling schemes are developed: one prioritizes the sensor with the smallest current AoI, while the other selects the sensor with the largest difference in adjacent AoI values. In the data upload phase, the problem is reformulated as a secrecy rate maximization task, where an iterative optimization algorithm, incorporating auxiliary variables, is designed to optimize the RIS reflection coefficients. Simulation results indicate that this strategy achieves an average AoI reduction of approximately 10 s compared to existing methods.

Similarly, the authors in [28] analyze a UAV-RIS-assisted maritime communication system in the presence of a malicious jammer, where the UAV-RIS is employed to jointly optimize positioning and RIS elements to maximize the system's energy efficiency (EE) while maintaining the quality of service (QoS) under jamming attacks. Additionally, an adaptive energy harvesting scheme is proposed, enabling simultaneous information transmission and energy harvesting to extend the UAV's operational endurance. To tackle the challenges of non-convex optimization and the complexities of maritime environments, a deep reinforcement learning (DRL)-based intelligent resource management strategy is introduced. This method jointly optimizes the base station's transmitting power, UAV-RIS positioning, and RIS beamforming. Furthermore, a hindsight experience replay mechanism enhances learning efficiency and system performance. Simulation results confirm that the proposed method surpasses conventional approaches in energy efficiency and energy harvesting across diverse real-world scenarios.

Additionally, the authors in [28] investigate the performance of an integrated air-to-underwater network employing an amplify-and-forward relay with variable gain, em-

phasizing the role of RISs in a hybrid terahertz (THz)–underwater optical communication system. The study models the fading effects and pointing errors on the THz signal using the α-μ distribution, while underwater optical turbulence is characterized by the exponential generalized Gamma distribution, which incorporates pointing error impairments. For performance evaluation, both heterodyne detection and intensity modulation with direct detection techniques are analyzed. Key performance metrics, including outage probability, average bit error rate, and average channel capacity, are derived analytically using the Meijer-G function, with high signal-to-noise ratio (SNR) approximations provided for deeper insights. Monte Carlo simulations validate the analytical findings, demonstrating the system's robustness across different modulation schemes, fading conditions, and receiver detection techniques.

3.3. Underwater Communications

Underwater communications, a relatively underexplored yet critical area, face unique challenges due to the highly absorptive nature of water and the presence of factors such as salinity, temperature gradients, and air bubbles. Traditional communication methods often struggle to achieve high reliability and efficiency in such environments. RIS technology offers a promising solution for improving communication performance in air-to-underwater and underwater-to-underwater scenarios by redirecting and focusing signal paths through RISs, as illustrated in Figure 4.

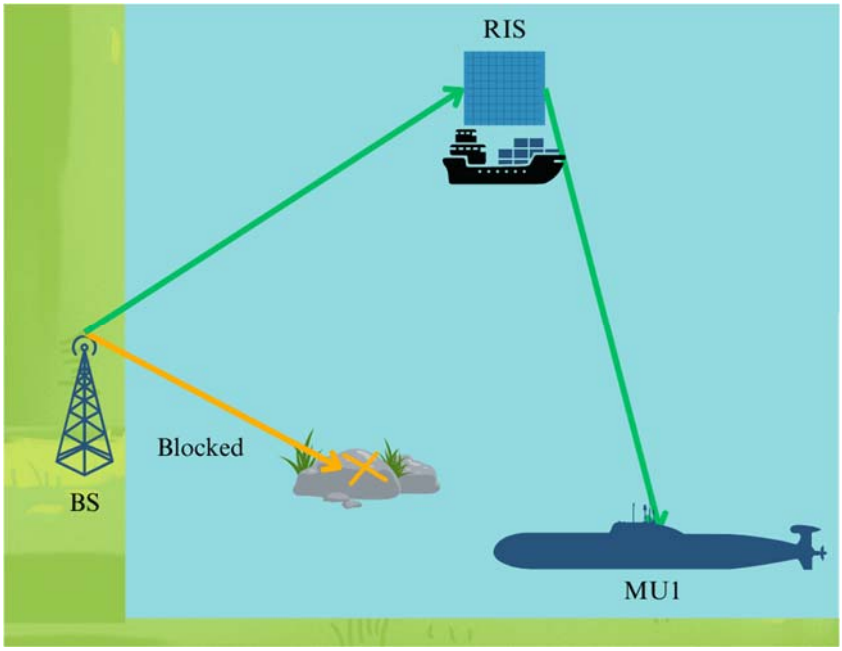


Figure 4. RIS-assisted B5G communications in underwater applications.

For example, the authors in [29] investigate the performance of an integrated air-to-underwater network employing an amplify-and-forward relay with variable gain, emphasizing the influence of RISs on a hybrid terahertz (THz)–underwater optical communication system. The study models the fading effects and pointing errors on the THz signal using the α-μ distribution, while the underwater optical turbulence is characterized by the exponential generalized Gamma distribution, incorporating pointing error impairments. To enable performance comparison, both the heterodyne detection technique and intensity modulation with direct detection are analyzed. Analytical expressions for key performance metrics, including outage probability, average bit error rate, and average channel capacity, are derived using the Meijer-G function. High signal-to-noise ratio approximations of these

metrics are also presented for deeper insights. Additionally, the impact of modulation schemes, fading severity, pointing errors, atmospheric turbulence, and receiver detection techniques on system performance is thoroughly evaluated. The analytical results are corroborated through Monte Carlo simulations, confirming the robustness and accuracy of the findings.

3.4. Challenges in RIS Deployment for Maritime Scenarios

Despite the huge potential, as depicted in the previous subsection, the deployment of RIS in maritime environments introduces several technical and practical challenges that must be addressed to ensure efficient and reliable operation. Maritime communications differ significantly from terrestrial networks due to the dynamic nature of the sea environment, harsh environmental conditions, security vulnerabilities, and regulatory constraints. These challenges require innovative engineering solutions and strategic adaptations to integrate RIS technology effectively into maritime networks. Table 2 also summarizes the challenges depicted in this subsection.

Table 2. Challenges in RIS deployment in maritime scenarios.

Challenge	Potential Solution	References
Environmental Factors	Use corrosion-resistant materials and protective coatings; implement robust hardware designs for maritime conditions.	[30,31]
Dynamic Topology and Mobility	Deploy real-time adaptive beamforming and tracking algorithms; use AI-based predictive models to compensate for vessel mobility.	[32–34]
Integration with Existing Systems	Develop RIS-compatible protocols that ensure interoperability with existing satellite and RF systems.	[35,36]
Security and Privacy Risks	Implement strong encryption, authentication mechanisms, and AI-based anomaly detection for maritime RIS.	[37,38]
Underwater Deployment Challenges	Explore alternative signal propagation methods such as acoustic and hybrid optical–acoustic systems.	[39,40]

Unlike land-based RIS installations, maritime RIS units are exposed to extreme environmental conditions. High humidity, saltwater exposure, strong winds, and temperature fluctuations can significantly degrade electronic components, leading to corrosion and reduced efficiency over time [30]. RIS panels need to be fabricated using corrosion-resistant materials, such as specialized composites or coatings, to prevent degradation. Furthermore, structural reinforcements may be required to ensure that RIS units can withstand high mechanical stress from waves and storms, particularly when mounted on ships or offshore platforms [30,31].

Another major challenge in maritime RIS deployment is constant motion. Unlike static infrastructure in urban environments, ships are constantly in motion, and their relative positions change rapidly. This results in frequent variations in the angle of arrival (AoA) and the angle of departure (AoD) for signals, causing traditional beamforming algorithms to become less effective [32]. To maintain optimal performance, RIS systems must be integrated with real-time feedback mechanisms that dynamically adjust their reflection coefficients based on vessel movement [33].

Moreover, RIS deployment for ship-to-ship (S2S) and ship-to-port (S2P) communications must consider long-distance propagation effects, including multipath fading and Doppler shifts. Advanced AI-driven optimization algorithms can help RIS track vessel movements and adapt the reflection parameters accordingly, ensuring stable connectivity even in highly dynamic environments [34].

Furthermore, maritime communication systems rely on a mix of satellite, radio-frequency (RF), optical, and underwater acoustic technologies. The challenge in RIS deployment is ensuring seamless integration with these existing infrastructures without causing disruptions. Unlike terrestrial networks, maritime networks use different frequency bands—for example, VHF for short-range communication, the Ka band for satellite communications, and acoustic waves for underwater transmissions. To maximize compatibility, RIS should support multi-band operations, allowing it to enhance different types of signals across various communication domains. Additionally, standardization efforts are necessary to create universal protocols that ensure RIS module efficiently in satellites and terrestrial base stations without interference [35,36].

When new network components, such RIS, are introduced, the potential security risks that these elements can face are multiple. Based on the authors of [37,38], these risks include the following:

- Unauthorized access and signal hijacking: if RIS elements are compromised, an attacker could manipulate the surface's reflection coefficients to reroute or block signals, leading to communication failures.
- Eavesdropping risks: RISs reflect signals in highly directional beams, but adversaries could exploit reflections to intercept confidential communications.
- Jamming and spoofing attacks: malicious actors could use intentional interference to disrupt the RIS-assisted links, posing a risk for autonomous navigation and critical maritime operations.

To mitigate these risks, end-to-end encryption, secure authentication mechanisms, and AI-driven anomaly detection algorithms must be implemented. Additionally, integrating blockchain-based access control could provide further security assurances for autonomous vessels and smart port infrastructures [39].

Especially for underwater scenarios, RIS-assisted underwater communications present additional obstacles. Unlike in air, electromagnetic waves experience severe absorption in water, particularly at high frequencies. This makes conventional RF-based RIS systems unsuitable for underwater use. Alternative solutions include the following [40]:

- *Acoustic RIS*: instead of reflecting RF signals, underwater RIS units could manipulate acoustic wave propagation to optimize data transfer between submerged sensors, submarines, or underwater robots.
- *Hybrid RIS systems*: a combination of RF and optical/acoustic technologies could be used, allowing RIS to bridge communication between aerial and underwater nodes.

However, challenges such as biofouling (marine organism accumulation), high water pressure, and extreme temperature variations must be addressed for long-term underwater RIS deployment. Advanced coatings and self-cleaning mechanisms could be developed to prevent biological degradation over time [40].

Finally, maritime communications are subject to strict international regulations from organizations such as the International Telecommunication Union (ITU), International Maritime Organization (IMO), and local national authorities. The lack of dedicated regulations for RIS deployment in maritime environments slows adoption and creates uncertainty for ship operators and service providers.

4. DL-Based Beam Selection in RIS B5G Maritime Environments

4.1. Maritime Use Case and System Model

As described in previous sections, in modern maritime operations, the advent of autonomous vessels is revolutionizing port and harbor activities. A critical aspect of these operations is autonomous mooring, where vessels safely and efficiently dock at

ports without human intervention [41,42]. Similarly, autonomous approaches involve precise navigation and communication between vessels and port infrastructure during docking procedures [43,44]. These processes require robust, low-latency, and high-reliability communication systems capable of handling dynamic environments and ensuring safety under stringent constraints.

The proposed autonomous mooring and approach use case necessitates seamless vessel-to-shore and vessel-to-vessel communication. Traditional maritime communication systems often fail to meet these requirements due to unpredictable signal propagation over water, interference from large metallic structures, and NLoS conditions introduced by port obstructions such as cranes and storage facilities [44]. Furthermore, dynamic elements such as vessel movement and environmental changes exacerbate these challenges, necessitating innovative solutions [45].

The proposed use case is depicted in Figure 5.

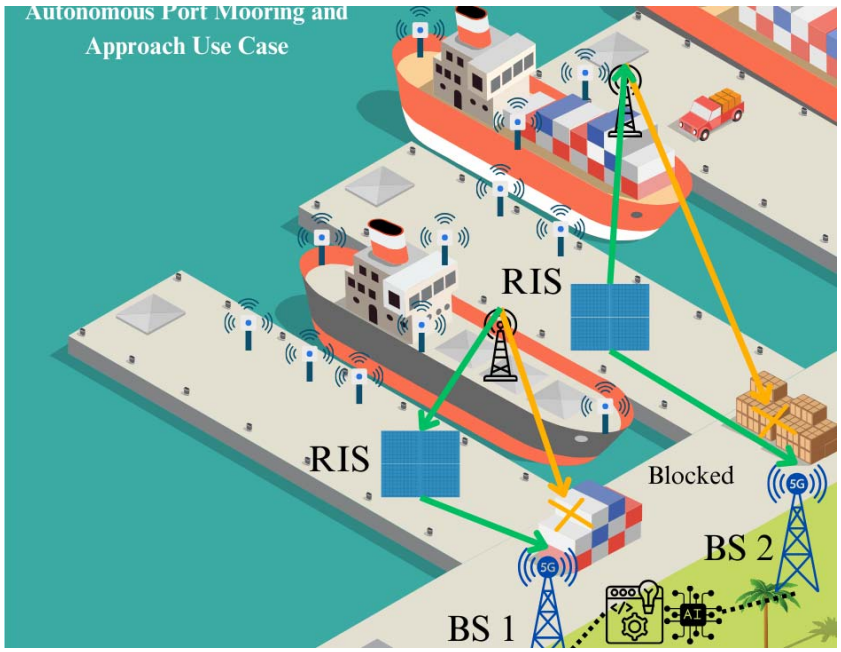


Figure 5. RIS and DL-assisted B5G-aided autonomous port mooring and approach use case.

On the one hand, RISs offer a transformative approach to overcome these limitations. By strategically deploying RIS on port structures, buoys, and even onboard vessels, it is possible to create programmable communication environments. This capability is particularly critical during autonomous docking, where continuous data exchange with minimal latency ensures vessel alignment, speed adjustments, and safe coupling with port infrastructure. On the other hand, DL further complements this framework by providing the computational intelligence to adapt RIS configurations in real time. By leveraging historical and real-time data, DL models can predict optimal beamforming patterns and RIS phase shifts, ensuring robust connectivity in diverse conditions. In the context of autonomous mooring, DL-based algorithms can anticipate channel state variations caused by vessel movement or environmental factors, dynamically adjusting RIS parameters to maintain communication quality. Similarly, for autonomous approaches, DL can optimize vessel-to-shore and vessel-to-vessel communication, enhancing situational awareness and coordination.

The downlink of an RIS-assisted wireless B5G/6G multicellular orientation is under evaluation, as depicted in Figure 6. The system model for this use case involves central BSs located at the port, equipped with multiple antennas for beamforming, and RIS units deployed on port structures and vessels. The RIS units are designed to operate in tandem

with the BS, enabling the real-time optimization of signal propagation paths. Autonomous vessels are equipped with communication modules that exchange data with the RIS and base station, facilitating efficient resource allocation and beam selection.

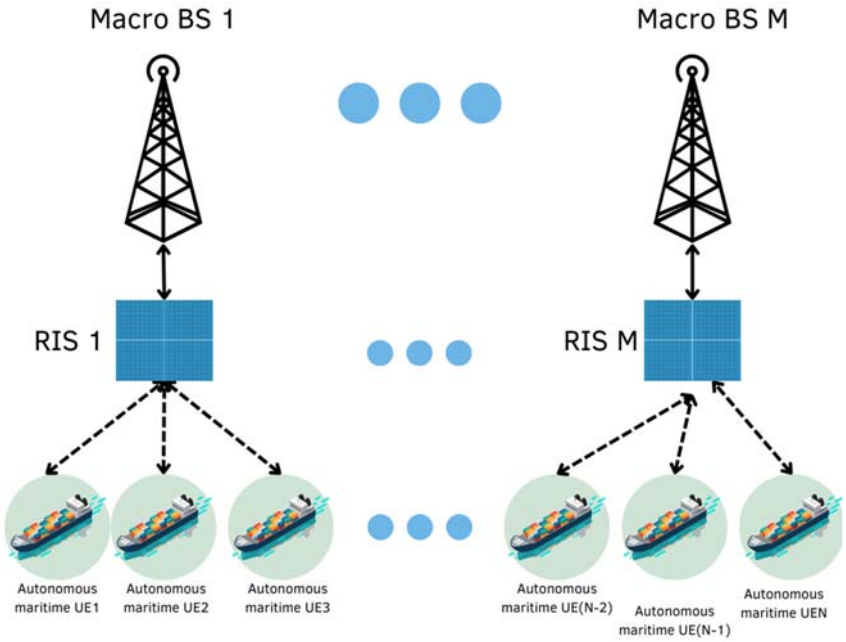


Figure 6. Two-hop maritime B5G/6G cooperative network with RISs.

As depicted in Figure 6, the B5G/6G maritime system consists of the following sets:

- $S_{BS} = \{BS_1, BS_2, \ldots, BS_M\}$, where M denotes the total number of macro-BSs in the topology.
- $S_{RIS} = \{RIS_1, RIS_2, \ldots, RIS_M\}$, where M also denotes the total number of RIS units in the topology.
- $S_{UE} = \{UE_1, UE_2, \ldots, UE_N\}$, where N denotes the total number of autonomous maritime UEs (ships) that sequentially reach the topology.

The three different types of potential links that exist in the system are as follows:

- $L_{b,r}$, where $b \in S_{BS}$ and $r \in S_{RIS}$, which denote a BS-RIS unit link.
- $L_{r,u}$, where $r \in S_{RIS}$ and $u \in S_{UE}$, which denote an RIS unit–UE link.

The received signal at the autonomous vessel is expressed as

$$y = h_d^H wx + h_r^H \Theta G wx + n \tag{6}$$

where h_d represents the direct channel between the BS and the vessel, h_r is the RIS–vessel channel, and G is the channel between the BS and the RIS. The RIS configuration matrix Θ dynamically adjusts the phase and amplitude of the reflected signals to ensure constructive interference, with its elements defined as $\Theta = diag\left(\beta_1 e^{j\varphi_1}, \ldots, \beta_1 e^{j\varphi_M}\right)$, where β_i and φ_i are the reflection amplitude and phase shift in the i-th RIS element, respectively. The vector w represents the beamforming weights applied at the BS; x is the transmitted signal, and $n \sim CN\left(0, \sigma^2\right)$ is the noise.

To maintain robust connectivity, the system jointly optimizes the beamforming vector w and the RIS reflection matrix Θ to maximize the signal-to-noise ratio (SNR):

$$SNR = \frac{\left\| h_d^H wx + h_r^H \Theta G wx \right\|^2}{\sigma^2} \tag{7}$$

Concerning the above, the total system throughput is given by [3]

$$R = W\left\{\sum_{b=1}^{M}\sum_{n\in S_{UE}}\log_2(1+SNR)\right. \quad (8)$$

where W is the total bandwidth. By using Equations (7) and (8), the overall system's energy efficiency and spectral efficiency (EE and SE) are defined as

$$EE = \frac{R}{p_{total}} \quad (9)$$

$$SE = \frac{R}{W} \quad (10)$$

where p_{total} is the total system's transmission power.

4.2. Deep Learning Architecture

The RIS-aided maritime communication system incorporates a DL-based framework to optimize beamforming and RIS phase configuration in real time. The DL model is hosted at the port's central BS and processes data transmitted by the autonomous vessels, including their position, velocity, and local channel state information (CSI). The DL framework leverages these data to predict optimal RIS phase configurations and beamforming vectors, ensuring robust and reliable communication links under dynamic maritime conditions.

The DL model architecture is designed as follows:

- ***Input layer***: the input to the model is a feature vector consisting of vessel-specific parameters: $x = \left[x_{pos}, y_{pos}, v_x, v_y, h_d, h_r, G\right]$, where x_{pos} and y_{pos} are the vessel's 2D coordinates; v_x and v_y are its velocity components; and h_d, h_r, and G are the channel coefficients of the direct, RIS-to-vessel, and BS-to-RIS links, respectively.
- ***Hidden Layers:*** The model comprises multiple fully connected layers, each with a rectified linear unit (ReLU) activation function. These layers extract high-level features from the input, enabling the model to learn complex relationships between the vessel's parameters and optimal RIS configurations. The last fully connected layer of the topology has a size of $Num_{beam_{pairs}}$, signifying the size of the outputs.
- ***Batch Normalization layers***: these layers are interspersed between fully connected layers to stabilize training and accelerate convergence by re-centering and re-scaling activations.
- ***Dropout Layers***: dropout regularization is applied to prevent overfitting by randomly deactivating a fraction of neurons during training.
- ***Output Layer***: the output layer predicts two sets of parameters:
  - $S_{beam_{pairs}}$, which is the set of $Num_{beam_{pairs}}$ for the BS-RIS link.
  - $L_{beam_{pairs}}$, which is the set of $Num_{beam_{pairs}}$ for the RIS–vessel link.

By using these outputs, the optimal beams are selected not only for the BS-RIS link but also for the RIS–vessel one. The DL model minimizes a combined loss function which accounts for SNR, EE, and SE maximization. As for the training process, the DL model is trained using a dataset constructed from extensive Monte Carlo simulations of the maritime environment. Dataset generation and model training are performed offline so that the autonomous mooring process is not computationally burdened by the ML process. Each sample in the dataset represents a unique vessel position, velocity, and channel realization, with corresponding optimal RIS configurations and beamforming vectors obtained via offline optimization algorithms. A stochastic gradient descent (SGD) method is employed for weight updates, with a learning rate of η that is adaptively tuned. The overall algorithm's steps are also depicted in Algorithm 1.

Algorithm 1. DL-based beam selection algorithm in the maritime environment

Offline dataset generation phase

Input: number of BSs/RISs M and number of vessels N; input parameters are depicted in Table 3.

Deterministic algorithm steps ($\forall m \in M$)

Step 1—Vessel topology: $\frac{N}{M}$ vessels (maritime UEs) are spread into each of the M BSs coverage area.

Step 2—Monte Carlo simulations: optimal $S_{beam_{pairs}}$ for each BS-RIS link and $S_{beam_{pairs}}$ **for the RIS–vessel link are computed.**

Step 3—Dataset Formulation: the dataset is formulated as having the following:

feature vector x for each user $n \in S_{UE}$;
output vectors: $S_{m,m}$ and $L_{m,n}$.

Training phase

Input: Dataset from Step 3 of the previous phase.

Offline training steps

Step 1—Train test split: The dataset is split into 80% training and 20% test.

Step 2—Deep Learning training: Training is performed based on the parameters in Table 4.

Step 3—Test evaluation: The SGD engine updates the DNN weights, with a learning rate if EE and overall test set accuracy are decreased compared to the previous training round. Otherwise, training stops.

Real-time prediction phase

Input: feature vector x for new-coming maritime users (vessels).

Output: output vectors $S_{m,m}$ and $L_{m,n}$ for the new-coming maritime users.

Evaluation: Top-K accuracy and overall EE and SE calculation.

Table 3. System parameters.

Parameter	Value(s)
Tier/number of cells/number of BSs	2/19/19
Number of RISs	4
Number of vessels	Up to 50
Frequency	28 GHz
Number of antennas per BS/UE	4/2/1
Cell radius	$500\sqrt{3}$ m
Antenna height (BS/UE)	25/1.5 m
UE indoor-to-outdoor ratio	0.8/0.2
NLOS probability (BS-RIS/RIS-UE link)	89/90%
Path loss threshold	120 dB
Antenna gains BS/UE	18/4
Subcarriers per vessel (maritime UE)	8
Subcarriers per BS	132
Subcarrier spacing	60 kHz

Table 4. DL algorithm parameters and environment variables.

Parameter	Value(s)
Number of hidden layers	6
Training/Test set split	80%/20%
Maximum Epochs for training	50
Minimum Batch size	500
Learning rate	0.001
Optimizer	Adam

5. Simulations and Performance Evaluation

This section presents the performance of the proposed DL-based beam selection model, as depicted in Section 4 and Algorithm 1. The proposed approach is evaluated based on a two-tier B5G/6G orientation, while the employed simulation parameters concerning the network topology, the pathloss models, the employed antenna orientations, and the overall communication environment are depicted in Table 3.

As for the DL model set-up, the relevant parameters are depicted in Table 4.

The performed simulations were implemented using MATLAB (R2024b release [46]) and the corresponding toolboxes (e.g., Communications Toolbox, Statistics and Machine Learning Toolbox, and Deep Learning Toolbox).

The proposed DL algorithm for beam selection is jointly evaluated for ML metrics, such as Top-K accuracy, and network ones, such as achievable EE and SE.

On both occasions, the performance of the proposed algorithms is assessed against a state-of-the-art k NN method, as well as with a random beam selection system.

5.1. Impact on ML Metrics

A key aspect when designing DL-based schemes not only in the B5G/6G wireless communications domain but in general is the achieved accuracy compared to other methods. For this purpose, the Top-K accuracy metric is used. Top-K accuracy is a performance metric often used in classification tasks, especially when the model outputs a ranked list of possible predictions [47]. Instead of evaluating whether the top (most confident) prediction is correct (as in Top-1 accuracy), Top-K accuracy measures if the correct answer is within the top K predicted classes. In beam selection for RIS-aided maritime networks, the system often deals with a large set of potential beams due to environmental dynamics (e.g., reflections, blockages, and maritime mobility) [48]. Thus, this metric is selected over the traditional accuracy and/or F1-score metrics.

The achieved Top-K accuracy of the proposed DL model against the state-of-the-art approaches is depicted in Figure 7.

Figure 7 shows that for $K = 27$, the accuracy is already around 90%, which depicts the effectiveness of the proposed DL-based approach for the beam selection task in RIS-aided B5G maritime environments. Moreover, the proposed approach overperforms the traditional kNN beam selection algorithm. For example, when $K = 30$, the kNN considers the 30 closest training samples; however, the number of distinct beam pairs from these samples is less than 30, and the accuracy levels cannot surpass 50%. Hence, the proposed approach overperforms both the kNN beam selector and the random beam selector.

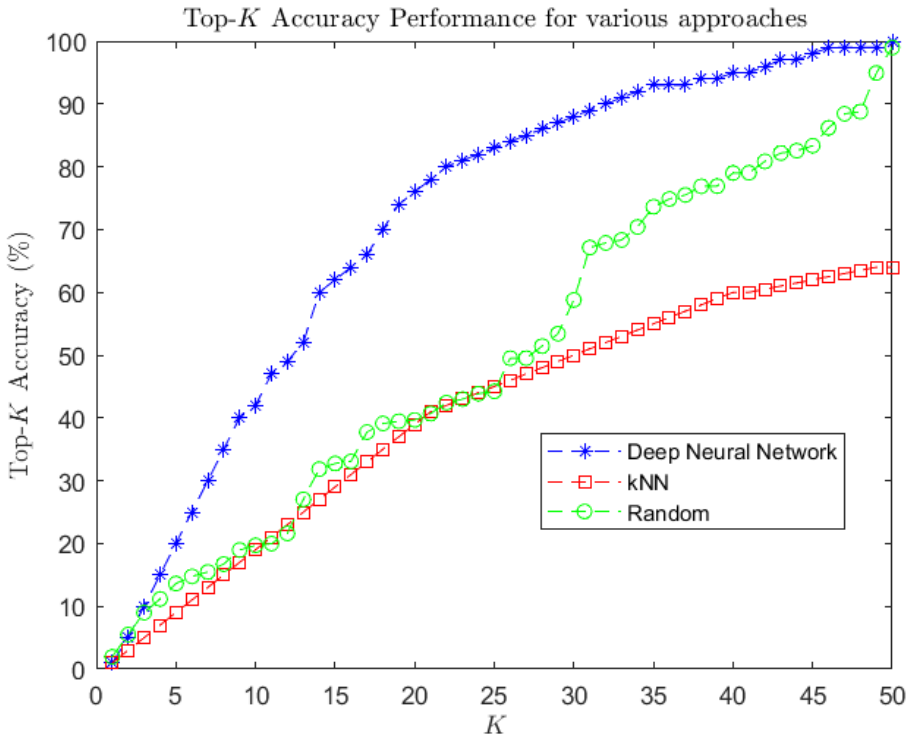


Figure 7. Top-K accuracy of the proposed DL-based beam selection model against different approaches.

5.2. Impact on Network KPIs

In ML-aided beam selection tasks, ML KPIs must be jointly evaluated along with network ones. For this purpose, Figure 8 depicts the overall system's EE levels for the proposed approach, along with the aforementioned reference simulation scenarios. Moreover, Figure 9 depicts the overall system's SE levels for these approaches.

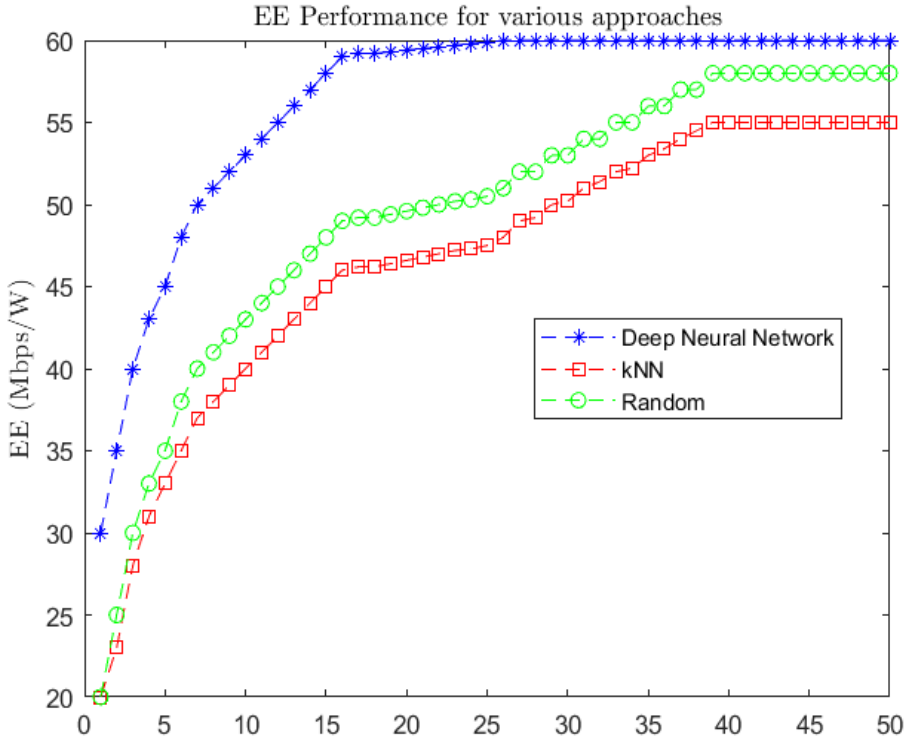


Figure 8. Mean total EE for the proposed DL-based approach and the reference scenarios.

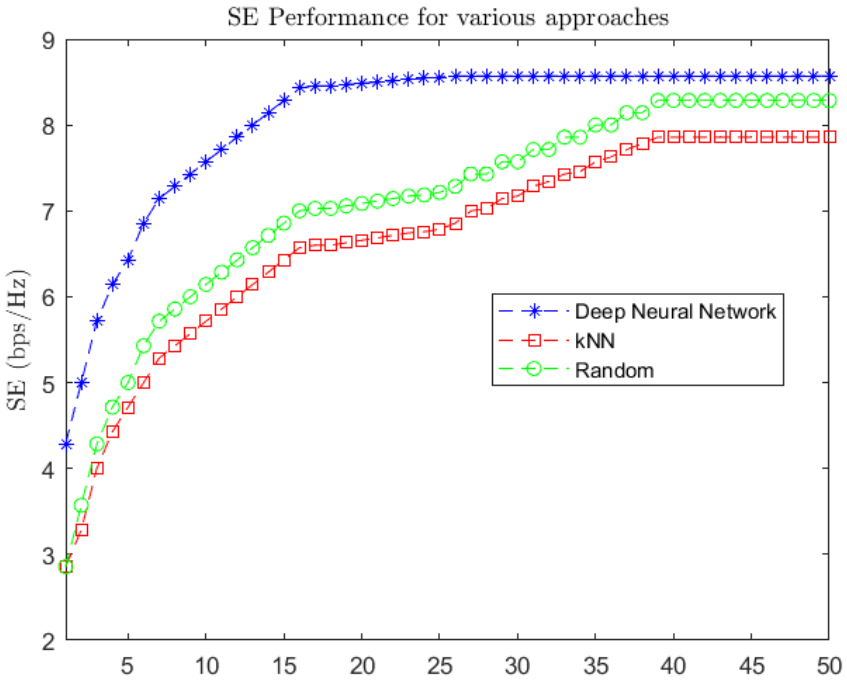


Figure 9. Mean total SE for the proposed DL-based approach and the reference scenarios.

As is evident from Figures 8 and 9, the utilization of the DL-enabled beam selection scheme can significantly improve key B5G/6G network metrics such as EE and SE in comparison to

- *The baseline scenario of random beam selection deployment:* When $K = 25$, the proposed scheme can achieve up to 60 Mbps/W EE levels, while the random beam selection scenario is limited to 50 Mbps/W. As for SE, the proposed scheme can achieve up to 8.5 bps/Hz, while the random beam selection scenario is limited to 7 bps/Hz. Thus, Figures 8 and 9 indicate a nearly 1.5 times improvement in total EE and a ~2 times improvement in total SE through the proposed DL-aided beam selection algorithm. The same or greater performance is indicated for smaller values of K. Thus, the proposed scheme generally achieves better B5G/6G network KPI performance compared to the baseline scenario.
- *The state-of-the-art kNN beam selector:* When $K = 25$, the proposed scheme can achieve up to 60 Mbps/W EE levels, while the kNN beam selection scenario is limited to 45 Mbps/W. As for SE, the proposed scheme can achieve up to 8.5 bps/Hz, while the kNN beam selection algorithm is limited to 6 bps/Hz. Thus, Figures 8 and 9 indicate a nearly 2 times improvement in total EE and a ~3 times improvement in total SE through the proposed DL-aided beam selection algorithm. The same or greater performance is indicated for smaller values of K. Thus, in general, the proposed scheme achieves better performance compared to this scenario.

5.3. Impact on Computation

A crucial factor in designing AI/ML algorithms in the context of B5G/6G networks, especially in highly volatile environments like maritime ones, is the effective trade-off that should be reached between ML KPI maximization and the computational resources needed for the training phase. Concerning these aspects, the proposed DL-based beam selection algorithm is developed:

- Using a standard MATLAB environment, with the simulation parameters depicted in Tables 3 and 4, the proposed DL model requires approximately 5 min for the training

phase of the algorithm. Once trained, the model can instantly determine the optimal beam based on the procedure depicted in Algorithm 1 (as outlined in Section 4.1).

- The baseline *k*NN model needs slightly less time to train the model, around 3 min. However, it is visible from Figures 8 and 9 that the performance is not as good as the proposed scheme's concerning either ML or network metrics. Thus, the examined trade-off of ML KPI maximization and computational resources needed is significantly better for the proposed scheme.
- For dataset generation, the overall execution takes around 2 h for a single round of 1000 Monte Carlo (MC) simulations. However, the training is performed offline, which means that there are no added latencies in the model's execution. Moreover, this phase is common for all methods, both the proposed one and the baseline scenario.

For the computational complexity of our proposed approach, we should co-evaluate both training and inference complexity. Training a DNN involves both forward and backward passes, while inference involves only the forward pass.

The total training complexity of the proposed DL-based beam selection scheme is computed as follows:

$$Training_{Compl_{DL}} = Comp_{forward} + Comp_{backward} \tag{11}$$

where $Comp_{forward} = O\left(\sum_{i=1}^{L} n_i * n_{i-1}\right) \approx O(Ln^2)$ and $Comp_{backward} = O(2Ln^2) = O(Ln^2)$. L denotes the total number of DNN layers, and n is the total number of neurons per layer. Backpropagation computes the gradients of weights, which involves an additional backward matrix multiplication per layer. This effectively doubles the complexity of the forward pass if the training runs for B samples per batch and E epochs. If there are N training samples, there are $\frac{N}{B}$ batches per epoch. Thus, Equation (11) becomes

$$Training_{Compl_{DL}} = O\left(E * \frac{N}{B} * Ln^2\right) + O\left(Ln^2\right) \approx O\left(Ln^2\right) \tag{12}$$

Inference involves only the forward pass, so its complexity per sample is

$$Inf_{Compl_{DL}} = O\left(Ln^2\right) \tag{13}$$

From Equations (12) and (13), the total computational complexity of our proposed scheme is $O(Ln^2)$.

As for the baseline model, kNN is a lazy learner, meaning that it does not perform explicit training. It simply stores all the training samples, so the training complexity is $O(1)$. To classify a new data point, kNN must compute the distance from the query point to all n training samples. The distance computation in a d-dimensional space takes $O(d)$ time. Sorting the distances to find the nearest k neighbors take $O(n)$ (using a max-heap for selection). Thus, the overall worst-case complexity for prediction is $O(nd)$.

Comparing our proposed approach's computational complexity with those of the baseline models, it is visible that the baseline model has a slightly better computational performance, which, of course, comes with the cost of performance degradation in terms of both ML and network KPIs, as depicted in Sections 5.1 and 5.2.

To conclude, the main outcomes from the performance evaluation of the proposed DL-based beam selection scheme in the RIS-aided autonomous mooring use case are depicted in Table 5.

Table 5. Key results from the performance evaluation of the proposed approach.

Metric	Result	Comparison with Baseline Methods
Achieved accuracy	Top- K accuracy over 90% for $K \geq 30$.	~2–3 times better performance for the same K compared to both kNN and random selection.
The system's overall EE	Considering $K = 30$, it achieves up to 60 Mbps/W.	~1.5–2 times better performance compared to both kNN and random selection.
The system's overall SE	Considering $K = 30$, it achieves up to 8.5 bps/Hz.	~2–3times better performance compared to both kNN and random selection.
Training time and model execution time	Needs around 5 min for model training and 2 h for offline dataset generation.	Comparable training times with the kNN baseline but achieves better ML and network metric performance.
Computational complexity	Slightly underperforms kNN.	However, this comes with a cost of performance degradation in the other metrics.

6. Conclusions

In this manuscript, the performance of a DL-based beam selection scheme for RIS-aided maritime orientations in B5G/6G networks has been evaluated. This is one of the first times that the B5G/6G enabling technologies, DL and RIS, are evaluated in the challenging, multi-criteria, and highly volatile maritime environment. Moreover, the overall scheme is proposed to be used in an autonomous mooring and/or autonomous approach use case scenario in port management topologies.

In terms of performance, the goal was to achieve an optimal trade-off between ML and network metric maximization. In particular, a DNN model that was trained using a dataset, which was generated via extensive Monte Carlo simulations, was considered to predict the best pair of beams for each maritime user/vessel that enters the port topology. The key novelty of the presented approach is that both EE and SE—as network metrics—and Top-K accuracy were considered in the evaluation phase. According to the performed evaluation, EE and SE levels can be jointly improved significantly compared to baseline approaches. Moreover, Top-K accuracy is improved by the proposed method. In terms of a more high-level perspective, the overall simulation set-up, which contains four port-based RISs, can effectively serve up to 50 vessels simultaneously entering the port in a coverage area of up to $500\sqrt{3}$ meters and speeds that correspond in JIT scenarios. Thus, B5G/6G RIS-aided solutions are proposed as a key enabler in "smart port management" scenarios.

As for potential future work on the domain, we would like to investigate Federated Learning (FL) methods in similar topologies, especially during the training phase of the algorithm. These methods promise even more gains in terms of the optimal utilization of the computational resources needed during the training phase. In this framework, future work concerns, among others, the utilization of FL and on-device ML task execution. Moreover, B5G/6G non-terrestrial (NTN) scenarios also need to be studied for the maritime domain. Finally, the execution of field tests using RIS in the maritime domain is also of interest to us.

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Acronyms

5G	Fifth Generation
6G	Sixth Generation
AI	Artificial Intelligence
AoI	Age of Information
B5G	Beyond Fifth Generation
DL	Deep Learning
DRL	Deep Reinforcement Learning
EE	Energy Efficiency
FL	Federated Learning
INTENT	Integrated Terrestrial/Non-Terrestrial
IoT	Internet of Things
JIT	Just-In-Time
KPI	Key Performance Indicator
LOS	Line-Of-Sight
MANETs	Mobile Ad hoc Networks
mMIMO	massive Multiple Input Multiple Output
mmWave	Millimeter-Wave
MUs	Maritime Users
NLoS	Non Line-of-Sight
NOMA	Non-Orthogonal Multiple Access
NTNs	Non-Terrestrial Networks
PLS	Physical Layer Security
QoE	Quality of Experience
QoS	Quality of Service
RISs	Reconfigurable Intelligent Surfaces
RRM	Radio Resource Management
SE	Spectral Efficiency
SGD	Stochastic Gradient Descent
SNR	Signal-To-Noise Ratio
UAV	Unmanned Aerial Vehicle
UxV	Unmanned Vehicle (aerial, sea, etc.)

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