Review

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Review

From 6G to *SeaX-G*: Integrated 6G TN/NTN for AI-assisted Maritime Communications – Architecture, Enablers, and Optimization Problems

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Abstract: The rapid evolution of wireless communications has introduced new possibilities for the digital transformation of maritime operations. As 5G begins to take shape in selected nearshore and port environments, the forthcoming 6G promises to unlock transformative capabilities across the entire maritime domain, integrating Terrestrial/Non-Terrestrial Networks (TN/NTN) to form a space-air-ground-sea-underwater system. This paper presents a comprehensive review of how 6G-enabling technologies can be adapted to address the unique challenges of Maritime Communication Networks (MCNs). We begin by outlining a reference architecture for heterogeneous MCNs and reviewing the limitations of existing 5G deployments at sea. We then explore the key technical advancements introduced by 6G and map them to maritime use cases such as fleet coordination, just-in-time port logistics, and low-latency emergency response. Furthermore, the critical Artificial Intelligence/Machine Learning (AI/ML) concepts and algorithms are described to highlight their potential in optimizing maritime functionalities. Finally, we propose a set of resource optimization scenarios, including dynamic spectrum allocation, energy-efficient communications and edge offloading in MCNs, and discuss how AI/ML and learning-based methods can offer scalable, adaptive solutions. By bridging the gap between emerging 6G capabilities and practical maritime requirements, this paper highlights the role of intelligent, resilient, and globally connected networks in shaping the future of maritime communications.

Keywords: 6G; AI/ML; Deep Reinforcement Learning; Maritime Communications; Non-Terrestrial Network; Space-Air-Ground Networks; UAV relaying; Underwater Network

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1. Introduction

1.1. The Emergence of 6G in Maritime Communications

Maritime Communication Networks (MCNs) play a crucial role in ensuring seamless connectivity for vessels, offshore platforms, and coastal infrastructures. Given that more than 90% of global trade is transported by sea, the ability to maintain reliable and high-speed communication is essential for operational efficiency, safety, and economic sustainability [1]. Reliable connectivity at sea enables critical functions such as real-time navigation support, ensuring vessels can operate efficiently while avoiding hazards and optimizing routes. Safety applications, including distress

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signaling, emergency response coordination, and weather monitoring, heavily depend on uninterrupted communication channels [2]. Furthermore, efficient logistics and supply chain management require continuous tracking of cargo, fleet coordination, and automated port operations, all of which are facilitated by advanced communication networks. Beyond operational aspects, crew welfare has become an increasing priority, with high-speed internet access providing remote healthcare, training opportunities, and connectivity with families, ultimately improving working conditions for seafarers [3]. As maritime operations become more data-driven and technology-dependent, the evolution of communication networks is essential to support the growing demands of the maritime industry.

Recent developments in MCNs have introduced several networking paradigms to address the challenges of connectivity across vast oceanic environments. Dominant among these are Low Earth Orbit (LEO) satellite-based networks, which offer global coverage with reduced latency compared to traditional geostationary satellites and are increasingly seen as a backbone for maritime broadband services (e.g., Starlink Maritime, OneWeb) [4]. In parallel, air-to-sea (A2S) communication networks enabled by high-altitude platforms (HAPs), unmanned aerial vehicles (UAVs), and even airborne base stations, are gaining traction for delivering high-capacity links to moving vessels within line-of-sight (LoS) ranges [5,6]. Coastal and offshore areas continue to rely on terrestrial cellular networks, including specialized 4G/5G deployments on oil rigs and port infrastructure. Additionally, ship-to-ship (S2S) and ship-to-shore (S2Sh) mesh-based communication systems are employed for local coordination and information dissemination, particularly in dense maritime traffic zones [2]. Hence, the current MCN architecture is inherently heterogeneous, combining satellite, aerial, terrestrial, and maritime ad hoc networks (MANETs), often with custom-built solutions to meet specific regional, economic, or operational needs. However, these disparate systems often suffer from fragmented interoperability, limited adaptability, and inconsistent quality of service (QoS), especially in dynamic maritime conditions. This diversity and fragmentation highlight the need for a unified, intelligent, and scalable communication framework, precisely where 6G technologies can make a transformative impact [7].

6G is expected to revolutionize maritime communication with higher data rates, ultra-low latency, and Artificial Intelligence/Machine Learning (AI/ML)-driven networks. Its integration of terahertz (THz) communication and intelligent reflecting surfaces (IRS) will enable seamless, high-speed, and ultra-secure connectivity [8]. AI-powered network automation will also enhance efficiency, optimizing bandwidth and reducing energy consumption. Since the maritime industry heavily relies on seamless and uninterrupted connectivity for navigation, safety, logistics, and operational efficiency, 6G becomes crucial for addressing the limitations of current networks. Unlike 5G, which depends on terrestrial infrastructure and satellite backhauls, 6G is expected to provide a fully integrated ecosystem combining terrestrial, satellite, aerial (i.e. HAPs and UAVs), and even underwater communication networks to enable global coverage, even in deep-sea regions [6]. This advancement is particularly critical for intelligent MCN resource management, autonomous shipping, real-time oceanographic data collection, remote port operations, and AI-driven decision-making for fleet management. Furthermore, the inclusion of smart, energy-efficient communication solutions will significantly reduce the operational costs of maritime connectivity [9].

1.2. Related Works

The evolution of MCNs has garnered significant attention, leading to various innovative architectures and technological advancements. Guan et al. introduced MagicNet, a novel architecture deploying seaborne floating towers in a honeycomb topology to provide wide-area and seamless maritime coverage, addressing the limitations of traditional shore-based base stations [10]. Also, UAVs have emerged as pivotal components in enhancing maritime communications. Nomikos et al. have provided a vision on UAV-aided maritime communications, discussing deployment considerations, applications, and future challenges, highlighting UAVs' potential in extending coverage and improving communication reliability [5,11]. Similarly, the integration of air-to-sea

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communication systems has been explored to enhance the Maritime Internet of Things (MIoT), focusing on enabling technologies and applications [6,12]. Hybrid communication models have also been proposed to enhance maritime connectivity. Wei et al. discussed hybrid satellite-terrestrial communication networks for the MIoT, emphasizing key technologies, opportunities, and challenges in achieving seamless integration [13]. Furthermore, the concept of space-air-sea-ground integrated networks has been examined for maritime transportation emergency forecasting, proposing a layered structure to support operational responses in distress scenarios [14]. Further, Xylouris et al. discussed the challenges and opportunities for MCNs in the 6G era, focusing on enabling technologies and relevant use cases [15]. To enable smart and collaborative shipping, Giannopoulos et al. introduced FedShip, a federated over-the-air learning framework designed for communication-efficient and privacy-aware operations in 6G maritime environments [16]. Apart from the aforementioned studies, Table 1 summarizes key recent works studying different aspects of 6G/MCN combined networks.

Table 1. Recent studies combining 6G/MCN concepts.

Study	Summary
[15]	Reviews enabling technologies, use cases, and challenges for 6G-enabled MCNs including smart ports and integrated network architectures.
[16,17]	Proposes a federated learning and over-the-air computation framework for privacy-aware, efficient 6G maritime communications.
[6]	Presents a comprehensive survey of air-to-sea integrated maritime IoT technologies, applications, and research gaps.
[18]	Explores UAV and satellite-supported base stations for maritime 6G coverage, focusing on link scheduling and rate adaptation.
[19]	Proposes resource allocation and task offloading solutions for reliable 6G space-air-sea maritime networks.
[20]	Surveys maritime wireless channel characteristics and network architecture differences from terrestrial systems.
[21]	Overviews 6G communication technologies, architectures, and applications, including implications for maritime connectivity.
[22]	Highlights underwater communications as a vital but overlooked infrastructure for achieving full 6G network access.
[5,11]	Examines UAV swarms with NOMA to enhance 6G maritime wireless connectivity and spectral efficiency.
[23]	Reviews path-planning for autonomous maritime vehicles to support data collection and NTNs in future oceanic 6G systems.

Despite these advancements, gaps remain in the literature, particularly concerning the adaptation of 6G enabling technologies to the unique challenges of maritime environments. Existing studies often focus on individual components or technologies without providing a holistic view of integrating 6G features into MCNs, including space-air-ground-sea-underwater layers. There is also a lack of studies describing both new applications and emerging optimization paradigms enabled by the 6G-enabled MCNs. This paper aims to bridge this gap by systematically examining how 6G technologies and applications, such as AI-driven networks, ultra-low latency communications, and advanced spectrum management, can be tailored to enhance MCNs, addressing current limitations and paving the way for future optimization and developments.

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1.3. Paper Scope and Structure

This paper aims to provide a comprehensive and forward-looking review of how 6G enabling technologies can be adapted and integrated into MCNs. The primary scope includes three core contributions. First, the paper introduces and analyzes a reference architecture for heterogeneous MCNs that spans space, air, sea surface, ground, and underwater layers, emphasizing the multi-domain interactions and technological heterogeneity of future maritime systems. Second, it surveys key communication technologies and techniques from the 5G/6G ecosystem such as Reconfigurable Intelligent Surfaces (RIS), Non-Orthogonal Multiple Access (NOMA), UAV relaying, THz communications, and AI-driven networking. The paper also discusses their potential applicability and adaptation to the unique challenges of maritime environments, including mobility, intermittent coverage, and harsh propagation conditions. Third, the paper identifies a set of representative optimization and resource management scenarios arising in MCNs, formulates them mathematically, and maps them to suitable solution methodologies, ranging from traditional optimization (e.g., convex programming, graph theory) to modern approaches such as machine learning, reinforcement learning, and federated learning.

Beyond these technical focuses, the paper also aims to bridge the gap between academic research and practical deployment by highlighting relevant applications, such as autonomous navigation, emergency response, remote monitoring, and smart shipping. It further explores different AI-based concepts that can be adopted to support and optimize maritime paradigms. The remainder of the paper is organized as follows: Section 2 presents the evolution of MCNs and introduces the proposed reference architecture. Section 3 reviews the fundamental enablers and emerging technologies of 6G by providing a multi-level vision of 6G networks. Section 4 outlines the emerging AI-driven concepts that can benefit maritime operations and optimization problems. Section 5 discusses potential applications that can be realized in future 6G MCNs. Section 6 proposes detailed technical solutions and optimization problems aligned with 6G capabilities. Finally, Section 7 concludes the paper and outlines future research directions.

2. Evolution of Maritime Communication Networks

2.1. Reference Architecture of multi-layered MCNs

The architecture of modern MCNs is inherently heterogeneous and multi-layered, integrating technologies across space, air, sea surface, underwater, and shore-based domains [10]. The reference architecture of a future MCN is illustrated in Figure 1, reflecting a multi-communication and heterogeneous ecosystem that spans across five major domains: space, air, sea surface, underwater, and ground [24]. These domains collaborate to provide ubiquitous, adaptive, and resilient connectivity to ships, unmanned systems, and maritime infrastructure. The architecture enables not only traditional communication but also modern 6G-era services such as autonomous navigation, real-time monitoring, and distributed AI. At the top layer, LEO satellites provide global connectivity, acting as the backbone for data relaying and backhaul connections, especially in deep-sea areas. Flying nodes, such as HAPs, UAVs and Balloons, constitute the aerial tier, offering low-latency, high-throughput links to ships, offshore platforms, and buoys. These platforms can host mobile BSs, relay nodes, or edge servers, supporting real-time communication and computation services [25].

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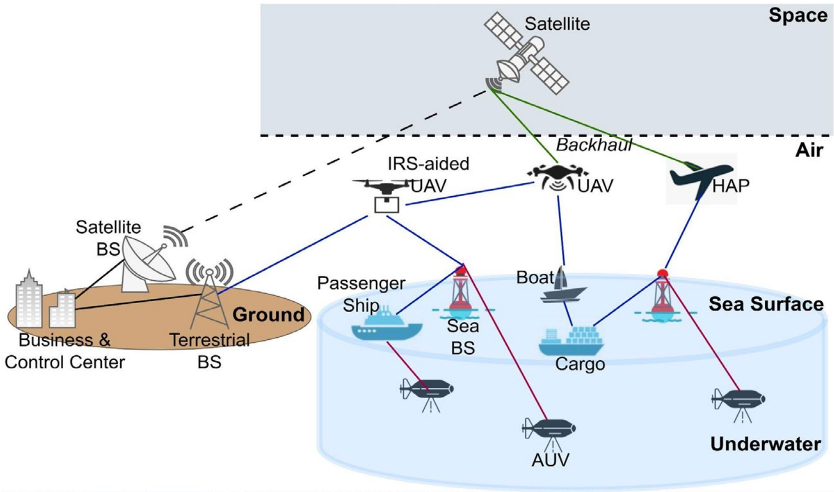

Figure 1. A reference architecture for multi-layered heterogeneous MCN.

On the sea surface, ships, buoys, and sea BSs form a dynamic network layer that handles short-to-medium range communication using a combination of terrestrial cellular (4G/5G), maritime VHF/UHF, and mmWave links. Channels for S2S and S2Sh connections use LTE, Wi-Fi 6, and specialized maritime communication bands to facilitate navigation coordination, data exchange, and crew connectivity [7,26]. Underwater communication is supported via acoustic links [27], optical communication [28], and magnetic induction [29], enabling interaction with AUVs and underwater sensors.

This reference architecture also reflects the increasing demand for edge intelligence, with edge computing nodes deployed on ships, buoys, UAVs, or satellite payloads to enable local processing, reduce latency, and support AI-driven services. The entire MCN system requires tight coordination of routing, resource allocation, and link scheduling, given the dynamic topology, diverse QoS requirements, and intermittent connectivity that characterize the maritime environment. Table 2 summarizes the key MCN entities and their roles.

Table 2. 6G-enabled MCN entities and their roles.

Layer	Entity	Role
Space	Satellites	LEO satellites provide global coverage and serve as the backbone for long-range backhaul communication. They offer connectivity to ships, UAVs, and coastal infrastructure, particularly in deep-sea areas with no terrestrial coverage.
Air	HAPs, UAVs	HAPs and UAVs operate in the aerial tier to support dynamic relay, coverage extension, and computation offloading. IRS-aided UAVs further enhance signal propagation using reconfigurable surfaces.
Sea Surface	Sea BS, Ships, Buoys	This layer includes passenger ships, cargo vessels, small boats, floating buoys, and Sea BS. These nodes engage in short-range S2S, S2Sh, and ship-to-aerial communication, forming the core of near-surface maritime networking.
Underwater	AUVs	AUVs and underwater sensors rely on acoustic or optical links to connect to sea surface nodes. These systems handle environmental monitoring, subsea inspection, and coordinated missions.

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Ground	Ground Infrastructure	Terrestrial base stations and satellite gateways connected to business/control centers act as the anchor points for centralized control, data aggregation, and global coordination of the MCN.

2.2. Communication Links and Technologies

The reference MCN architecture incorporates a rich set of multi-domain communication links, each with specific performance targets, propagation characteristics, and suitable technologies [20,30]. This subsection elaborates on the functional roles and enabling technologies of each major link category in the space–air–ground–sea–underwater network, as shown in Figure 1. Below, a vision of the different link categories is described, whereas a summary of all communication links per MCN domain is listed in Table 3 [30].

1. **Satellite to Ground Communication:** This link connects satellites to terrestrial stations or control centers, serving as the global backhaul for data traffic, remote control, and coordination. Satellite Base Stations (Sat-BS) use L, Ku, Ka, and Q/V bands, with newer 6G systems exploring optical satellite communication for extremely high-throughput and low-latency links. These links require robust atmospheric compensation and precise beam steering to maintain high performance [31].
2. **Satellite to UAV/HAP Communication:** Satellites also interface with HAPs and UAVs to extend coverage in areas with no direct ground access. These links are critical for data offloading, relaying, and supporting edge computing in the sky. Communication is typically realized via mmWave backhaul (e.g., Ka/Q/V bands) or laser communication systems, enabling high-rate data transfers and latency-sensitive coordination.
3. **UAV/HAP to Ship/Sea BS Communication:** Airborne platforms such as UAVs and HAPs establish air-to-sea links with moving vessels and floating platforms (e.g., buoys or Sea BS). These links may leverage sub-6 GHz for robust coverage and mmWave or THz for high-throughput, low-latency applications. Reconfigurable Intelligent Surfaces (RIS) mounted on UAVs or buoys can dynamically optimize beam directionality and link quality in challenging maritime conditions.

Table 3. Communication links and operating bands for different MCN interfaces.

Link	Technology	Frequency Band
Satellite ↔ Ground	SATCOM, Ka/Q/V-band, Optical Comm	L, Ku, Ka, Q/V, Optical
Satellite ↔ HAP/UAV	LaserComm, mmWave, Backhaul	Ka/Q/V bands, Optical
HAP/UAV ↔ Ships/Sea BS	mmWave, THz, Sub-6 GHz, IRS-assisted links	3.5 GHz, 28 GHz, >100 GHz (THz)
Ground BS ↔ Ships (Nearshore)	5G NR, LTE, MIMO	Sub-6 GHz, 24–28 GHz
UAV ↔ UAV, UAV ↔ IRS UAV	mmWave/THz, RIS beam coordination	60 GHz, >120 GHz
Ship ↔ Ship / Buoy (S2S)	LTE, Wi-Fi 6, VHF/UHF	156–174 MHz (VHF), 2.4/5 GHz, LTE bands
Ship/Buoy ↔ AUV (Underwater)	Acoustic, Optical, Magnetic Induction	kHz (acoustic), 450–550 nm (optical), LF EM
Buoy ↔ Satellite	SATCOM, Ka/Q/V	Ka, Q/V

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4. **Ground BS to Ship Communication:** In nearshore waters or harbor zones, terrestrial 5G base stations provide service to ships using 5G NR, massive MIMO, and beamforming technologies. Operating mainly in sub-6 GHz and mmWave (e.g., 24–28 GHz) bands, these links support high-bandwidth and real-time services such as video surveillance, automated docking, and data offloading. However, they are subject to coverage limitations due to the curvature of the Earth and sea-level obstructions.
5. **UAV to UAV, or UAV to IRS-UAV Communication:** This category supports aerial mesh networking among UAVs, often using directional mmWave or THz links for rapid data exchange, fleet coordination, and redundancy. RIS-equipped UAVs can help reflect or boost weak signals when direct LoS is unavailable, supporting multi-hop relaying and network robustness.
6. **Ship-to-Ship and Ship-to-Buoy (S2S/S2Sh) Communication:** Ships, buoys, and other sea surface elements communicate over short-to-medium distances using Wi-Fi 6, LTE, 5G, or legacy VHF/UHF radios. These links support real-time situational awareness, collaborative routing, maritime traffic safety, and IoT-based sensor communication. They operate in Industrial, Scientific, and Medical (ISM) bands (2.4/5 GHz) and dedicated maritime VHF bands (156–174 MHz).
7. **Ship/Buoy to Underwater Communication:** Underwater links are primarily supported by acoustic communication, which enables low-data-rate but long-distance propagation. In short-range scenarios, optical blue-green links (450–550 nm) provide higher data rates with tight alignment constraints [28]. Magnetic induction is used for very short-range, high-reliability exchanges, such as docking or underwater sensor data harvesting [29].
8. **Buoy to Satellite Communication:** Floating buoys equipped with satellite modems serve as relay nodes for data from underwater sensors or ships in remote areas. These links typically operate in Ka-band or Q/V bands, offering connectivity to satellites even when other networks are unavailable.

This categorization of the communication links provide a foundation for identifying key challenges in maritime connectivity and motivates the need for intelligent optimization and 6G-enabling solutions, which will be discussed in later sections.

2.3.5. G/6G-Enabling Technologies

To meet the diverse demands of this complex and heterogeneous architecture, several enabling technologies coming from 5G or envisioned for 6G are essential [8]. As listed in Table 4, the ongoing evolution toward 5G/6G networks introduces a wide range of enabling technologies across the domains of communication, computing, and AI-driven control. These technologies aim to address the pressing challenges of MCNs, including intermittent coverage, high mobility, energy constraints, and diverse QoS requirements by offering intelligent, adaptive, and ultra-reliable communication infrastructures.

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Table 4. Potential domain-specific 5G/6G enabling technologies and their benefits to MCNs.

Domain	Enabling Technology	Benefit to MCNs
Communication	RIS Communications	Enhances NLoS links via UAVs or buoys, useful in harsh sea propagation conditions.
	NOMA Communications	Increases spectral efficiency for dense S2S/S2Sh sensor deployments.
	THz Communications	Enables ultra-high speed short-range links (e.g., UAV-to-ship).
	Full-Duplex (FD)	Improves bandwidth efficiency in ship relays and sea BS.
	Massive MIMO	Enhances directional communication with beamforming from shore to moving vessels.
Computation & Edge Intelligence	MEC	Real-time processing on ships, UAVs, sea BS to reduce latency and satellite load.
	Task Offloading	Offload compute-heavy tasks (e.g., analytics) from vessels to aerial/satellite nodes.
	Digital Twins	Create predictive models for ship operations and sea conditions using real-time data.
	Federated Learning (FL)	Enables decentralized AI among ships and nodes without sharing raw data.
AI-Driven Networking	Reinforcement Learning (RL)	Optimal routing, power control, and scheduling in dynamic maritime topology.
	AI-based Resource Allocation	Bandwidth and spectrum optimization across links and platforms.
	AI-based Spectrum Sensing	Detects interference, adapts to regulatory constraints in shared bands.
	AI-based Energy Management	Extends UAV and AUV operation through adaptive control strategies.

From a communication perspective, technologies like RIS, Non-Orthogonal Multiple Access (NOMA), massive MIMO, and THz communication aim to improve spectral and energy efficiency, provide reliable non-line-of-sight (NLoS) communication, and support high-density maritime scenarios [8,11,32]. These are particularly beneficial in dynamic sea environments with fluctuating link quality and sparse infrastructure.

In the computation domain, advancements such as Mobile Edge Computing (MEC) and task offloading enable near-real-time processing of data onboard ships, UAVs, and buoys, reducing dependence on high-latency satellite links [33,34]. Techniques like federated learning and digital twins enable decentralized, privacy-preserving AI and simulation-driven planning, essential for remote and autonomous operations at sea [35].

AI-based solutions contribute to adaptive control, resource optimization, and decision-making in MCNs [36]. These include reinforcement learning for dynamic routing and power control, AI-based spectrum sensing for interference avoidance, and energy management systems to extend the operational lifetime of UAVs and AUVs. By embedding intelligence into the network stack, these tools provide the scalability and agility required for large-scale maritime deployments. Collectively, the integration of these technologies positions 6G as a transformative enabler for future maritime networks, helping overcome bottlenecks and enabling a new generation of smart, autonomous, and resilient maritime services.

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2.4. Current Challenges and Limitations in MCNs

The deployment of 5G in maritime environments is currently in an exploration phase, with several pilot projects and feasibility studies underway. For example, 5G-VINNI [37] and 5G-ACIA [38] initiatives have proposed maritime testbeds that integrate 5G base stations on coastal infrastructure and seaborne platforms. In East Asia, South Korea has launched projects to provide 5G-based infotainment and operational services on ferries, while European ports are exploring private 5G networks for port automation and vessel tracking [39]. These implementations typically combine terrestrial 5G coverage with satellite backhaul to extend service into nearshore maritime zones.

The advantages of 5G for MCNs are numerous: enhanced bandwidth, low-latency communication, support for massive IoT, and network slicing for traffic prioritization. 5G also introduces MEC capabilities that can reduce response times and enable on-site data analytics for maritime use cases such as video surveillance, real-time navigation assistance, and remote diagnostics [2]. However, maritime deployment of 5G faces unique challenges. Coverage is limited by the absence of terrestrial infrastructure in open waters, necessitating hybrid solutions involving UAVs, ships-as-BSs, or satellite connectivity. Channel modeling over the sea is also more complex due to the reflection and scattering effects of water surfaces [30]. Furthermore, handover management for fast-moving vessels and UAVs remains a critical research issue, as standard terrestrial mobility protocols often fall short in maritime conditions.

Based on the above, despite the advances brought by 5G and hybrid satellite-terrestrial architectures, current MCN implementations still exhibit significant limitations. One of the primary concerns is coverage, particularly in deep sea and polar regions where terrestrial and even satellite connectivity may be intermittent or highly latency-inefficient. LEO satellites, while promising, still require dense constellations and reliable inter-satellite links, which are costly and technically challenging to maintain. Moreover, network densification and resource sharing introduce interference management problems, especially in nearshore zones with overlapping coverage from different sources (e.g., ports, ships, UAVs). Spectrum scarcity, exacerbated by regulatory fragmentation across maritime jurisdictions, further complicates the efficient use of available communication resources.

From an optimization standpoint, existing technologies are ill-suited to handle the highly dynamic and mobile topology of MCNs [2]. Conventional routing, power control, and scheduling algorithms assume relatively stable nodes and known traffic patterns, which are assumptions that do not hold in real-world maritime scenarios [13]. Additionally, QoS provisioning becomes complex due to varying latency, bandwidth, and reliability requirements across applications (e.g., remote sensing vs. telemedicine) [2,15]. Security and trust management also remain underdeveloped, especially with the growing reliance on distributed AI and edge computing in vessels and aerial platforms. These limitations highlight the urgent need for intelligent, flexible, and adaptive communication frameworks, where 6G technologies can play a central role in rethinking MCN design and operation [40].

3. Overview of 6G Technologies

This section introduces the fundamental vision of 6G and outlines its key features, multi-layer architecture, and core enabling technologies. It also highlights how each innovation is tailored to address current limitations in wireless networks and presents emerging 6G applications across different verticals.

3.1. Key 6G Features

6G networks aim to go beyond the enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable low-latency communication (URLLC) introduced by 5G,

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toward a fully intelligent, adaptive, and immersive communication system. Below, we present the main features of 6G, the gaps they address, and the expected benefits.

1. **THz Communications** [41]: THz bands promise to overcome the bandwidth limitations of existing mmWave systems by enabling ultra-high-speed links with terabit-per-second throughput and microsecond-level latency. This is especially useful for short-range, high-data-rate applications such as UAV-to-ship or UAV-to-HAP transmissions in dense maritime scenarios.
2. **AI-Native Network Architecture** [42]: Unlike 5G, which relies on external AI-based management tools, 6G is envisioned to have intelligence built into its core. This allows for real-time self-optimization, predictive resource allocation, and autonomous fault management—key requirements for supporting highly mobile and infrastructure-sparse maritime environments.
3. **RIS-assisted Propagation** [43]: RIS technology introduces intelligent reflective surfaces that can manipulate signal propagation to enhance coverage and signal strength. Deployed on UAVs or buoys, RIS can dynamically compensate for NLOS conditions and improve energy efficiency across maritime links.
4. **Integrated Sensing and Communication (ISAC)** [44]: By merging radar sensing and communication into a unified system, ISAC allows maritime platforms to simultaneously detect, track, and communicate. This dual capability can support object avoidance, environmental awareness, and seamless data exchange with minimal spectrum overhead.
5. **Ubiquitous Connectivity via Non-Terrestrial Networks (NTNs)** [45]: 6G integrates satellites, UAVs, and high-altitude platforms to create a truly global network fabric. For MCNs, this ensures reliable communication even in remote oceans, polar routes, and disaster-struck zones where terrestrial infrastructure is unavailable or inoperable.
6. **Blockchain and Post-Quantum Security (PQS)** [46]: To meet the growing demand for secure and tamper-proof maritime communication, 6G will incorporate blockchain for decentralized trust and post-quantum cryptographic algorithms to resist emerging threats from quantum computing.
7. **Digital Twins for Network and Platform Optimization** [47]: 6G enables the real-time synchronization of physical maritime systems such as ships, sensors, and networks—with their virtual counterparts. These digital twins can be used for predictive maintenance, energy optimization, and operational simulations, significantly enhancing situational awareness and decision-making.
8. **Joint Communication and Compute Co-Design** [33]: Rather than treating communication and computation separately, 6G co-optimizes them to reduce latency and improve reliability. This is particularly advantageous in MCNs, where real-time edge intelligence onboard ships or UAVs is necessary to reduce dependence on delayed satellite links.

3.2. General Multi-Level 6G Architecture

6G networks are envisioned as multi-level hierarchical architectures, comprising different layers of computation, communication, control, and intelligence [8,48]. Figure 2 illustrates a generic hierarchical 6G architecture, which can be described as follows:

1. **Physical Infrastructure Layer:** At the bottom of the architecture lies the physical infrastructure, consisting of diverse communication and sensing elements such as terrestrial BSs, UAVs, HAPs, satellites, underwater nodes, vehicles, and RISs. This layer is responsible for signal generation and propagation, physical layer access, 3D coverage deployment across ground, air, sea, and

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underwater domains. Key enabling technologies at this layer include THz communication links for ultra-high-speed transmission, massive MIMO for spatial multiplexing and beamforming, RIS for energy-efficient signal redirection, UAVs/HAPs/satellites for non-terrestrial and 3D global coverage [41].

2. **Network Control & Orchestration Layer:** The next layer hosts the control and management functions needed to operate and coordinate the underlying physical resources. It introduces intent-based networking, where high-level objectives are translated into optimized network configurations, potentially using AI-driven orchestration [48]. This layer performs resource allocation and slicing, mobility management and handover control, topology reconfiguration and adaptive routing, energy-aware and reliability-sensitive decisions. Key technologies that are supported in this layer include AI-based orchestration frameworks, federated learning for distributed control, autonomous network management agents and policy engines.
3. **Edge-Cloud & Distributed Intelligence Layer:** A key innovation of 6G lies in the distribution of intelligence and computation across multiple layers of the network—from cloud to edge to far-edge [34]. This allows network nodes such as ships, UAVs, or buoys to process data locally, reducing latency and improving resilience in disconnected or delay-tolerant scenarios. This layer supports real-time AI model inference and training at the edge, offloading decisions between ship-side, UAV-based, or cloud-based nodes, local predictive analytics (e.g., for route optimization, system failures). Enabling technologies include MEC, digital Twins for ships and platforms, FL for privacy-preserving AI, Swarm intelligence and Deep Reinforcement Learning (DRL) for adaptive control.
4. **Applications & Services Layer:** At the top of the stack, this layer interfaces directly with vertical sectors that will benefit from 6G's enhanced capabilities. These services are not only bandwidth-intensive but also latency-critical and reliability-sensitive, requirements which are central to 6G's design. Typical applications include smart shipping and autonomous navigation, healthcare (e.g., remote diagnostics, tele-surgery), Extended Reality (XR) and immersive entertainment onboard, remote control of autonomous maritime assets, predictive maintenance of ships and offshore platforms [15]. As such, this layer emphasizes cross-domain integration, enabling AI models and services to span edge devices, the cloud, and application endpoints seamlessly.

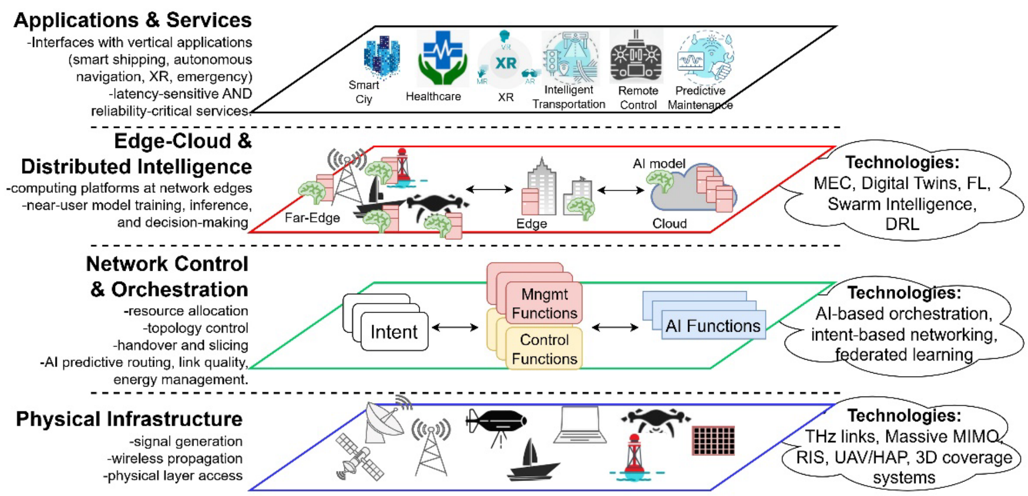

Figure 2. High-level Multi-layered 6G Architecture.

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4. AI-Driven Concepts in MCNs

AI/ML techniques are becoming fundamental components of next-generation communication networks, including 6G-enabled MCNs. In maritime environments, where operations are often remote, dynamic, data-rich, and safety-critical, the ability to autonomously learn, predict, and adapt is crucial [2,15]. This section introduces the essential AI/ML paradigms, starting from foundational concepts, and explains their application potential in MCNs, addressing use cases such as routing, anomaly detection, predictive maintenance, and decision support.

In principle, AI/ML refers to a set of algorithms that learn from data to make predictions or decisions without being explicitly programmed. ML can be broadly categorized into *Supervised Learning* (i.e., algorithms that learn from labeled data with known input-output pairs), *Unsupervised Learning* (i.e., models discover patterns in unlabeled data such as clustering), *Semi-Supervised Learning* (i.e., algorithms that combines small amounts of labeled data with large unlabeled datasets), *Reinforcement Learning* (i.e., agents that learns through interactions with an environment via rewards/punishments), *Self-Supervised Learning* (i.e., models that use the structure within the data itself to generate pseudo-labels) [49]. There might be also multi-model techniques such as *Federated Learning*, which involves training multiple models across decentralized devices while preserving data privacy [50]. In the context of MCNs, these approaches can be used to optimize routing, manage scarce spectrum, detect faults, predict maintenance, or make decentralized control decisions across a large network of ships, UAVs, buoys, and satellites.

4.1. Conventional AI/ML Methods

Supervised learning (SL) is best for well-defined problems with historical data (e.g., predicting equipment failures, classifying anomalies) and involves training a model on a dataset where each input is paired with a known output or label. The model learns to predict this output for unseen data. It is most effective when large volumes of labeled data are available. The general SL workflow is depicted in Figure 3. In the maritime domain, Supervised learning can be used for multiple reasons such as:

- **Predictive maintenance:** By labeling historical sensor readings (e.g., vibrations, temperature) with failure events, supervised models (like Random Forests or Neural Networks) can predict when components like engines or communication modules are likely to fail [35].
- **Vessel/Traffic classification:** Based on features like movement patterns, communication signatures, or radar echoes, ships can be automatically categorized (e.g., cargo, tanker, fishing) to assist with traffic control or border security [51].
- **Weather-aware routing:** SL models can learn to forecast wave height, storms, or sea temperature patterns, based on labeled environmental data. This may help to learn optimal paths and predict environmental hazards based on historical weather and performance outcomes [52].

These predictive tasks may be implemented by algorithms such as Linear Regression, Decision Trees, Support Vector Machines (SVMs), Random Forests, Neural Networks (e.g., Multilayer Perceptrons), Support Vector Machines (SVMs), Gradient Boosting Machines (e.g., XGBoost) [49].

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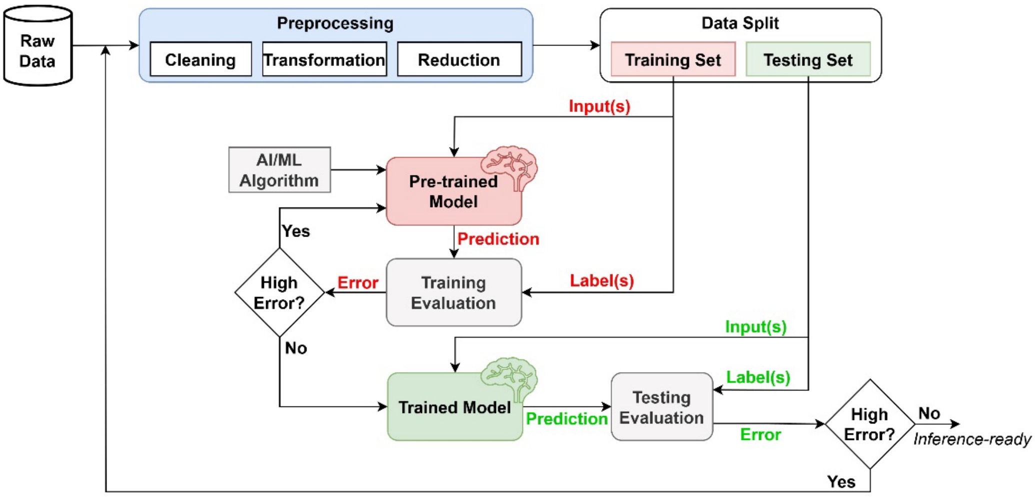

Figure 3. Generalized Supervised Learning workflow.

Unsupervised Learning (UL) and Semi-Supervised Learning (SemiSL) methods are valuable when labeled data is scarce, which is a common scenario in MCNs due to the cost of data labeling in remote or high-risk environments. UL operates on unlabeled data, attempting to uncover hidden patterns or structure, as illustrated in Figure 4. As is often the case for deep-sea operations or rare fault conditions, anomalies need to be detected, including unusual ship movement, communication silence, or off-route behavior. On the other hand, SemiSL uses a small amount of labeled data and a large pool of unlabeled data to improve learning efficiency. Both methods enable a variety of ML functions in the MCN sector, including:

- **Anomaly detection:** With UL, it is feasible to identify unusual communication or behavior patterns (e.g., sudden route deviation) [53].
- **Clustering for traffic modeling:** Clustering algorithms (like K-Means, DBSCAN) can group ships by trajectory behavior to identify outliers [54].
- **Sensor data compression:** UL can also cluster sensor streams with similar characteristics to compress data before satellite uplink, saving bandwidth [55]. This can be done by Principal Component Analysis (PCA) or autoencoders which can learn compact representations of sensor data and flag unusual deviations from typical patterns as potential faults or security threats.
- **Ship activity classification with low-size data:** Given that acquiring labeled data from resource-constrained devices (e.g., from AUVs or remote sensors), SemiSL may help to train a behavior classification model with limited expert-labeled data and automatically generalize to new traffic data [56].
- **Early fault detection:** SemiSL can use a few known fault events to improve recognition across large unlabeled sensor datasets [57].

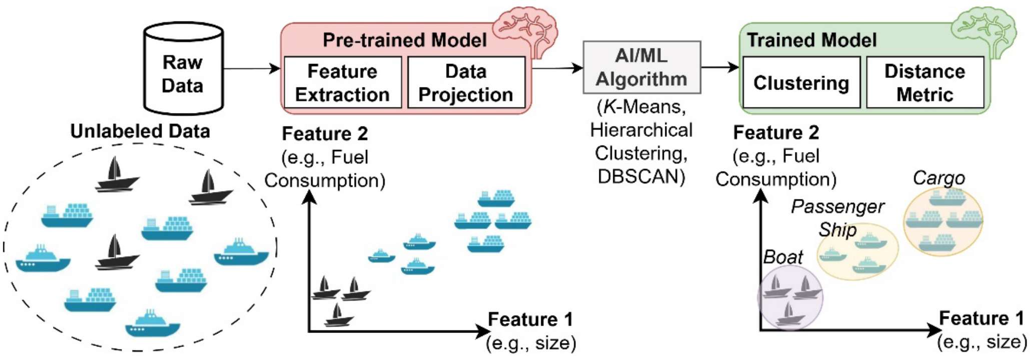

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Figure 4. Unsupervised Learning-based clustering of vessel types.

4.2. Decision-Making AI/ML Methods

Unlike conventional predictive and clustering methods, AI/ML can be also used to provide intelligent decision-making policies. Reinforcement Learning (RL) enables agents (e.g., ships, controllers, UAVs, BSs) to learn through trial and error, optimizing policies based on long-term rewards [58]. It is a paradigm where one or multiple agent(s) learn(s) to make decisions by interacting with an environment and receiving feedback in the form of rewards. An indicative RL interaction cycle is shown in Figure 5, where the RL optimizes the UAV 3D trajectory to maximize sea users' QoS based on a multivariate state vector. Deep RL (DRL) combines RL with deep learning, allowing it to handle large and continuous state/action spaces. In MCNs, RL/DRL can be applied indicatively to:

- **Dynamic adaptive routing:** Ships or UAVs can learn optimal routing strategies that minimize fuel use, avoid congestion, or maintain strong communication links in changing sea/weather conditions [58].
- **Power control and spectrum management:** In networks where resources are shared (e.g., RIS-assisted UAV relays), agents can learn to allocate power or frequency dynamically for maximum efficiency (e.g., maximize throughput and minimize interference) [59].
- **UAV/AUV path planning:** UAVs can learn energy-efficient mission paths while maintaining data links. Underwater vehicles operating in hostile, GPS-denied environments can learn robust paths that conserve energy while maintaining intermittent connectivity with sea BSs or buoys [60].
- **Fleet coordination:** Learn optimal positioning and relaying strategies among collaborative vessels and UAVs to improve network throughput and reliability [61].

Popular RL techniques include Q-Learning, Deep Q-Networks (DQN), Policy Gradient, Proximal Policy Optimization (PPO), and Actor-Critic methods, which are particularly effective in these sequential decision-making tasks.

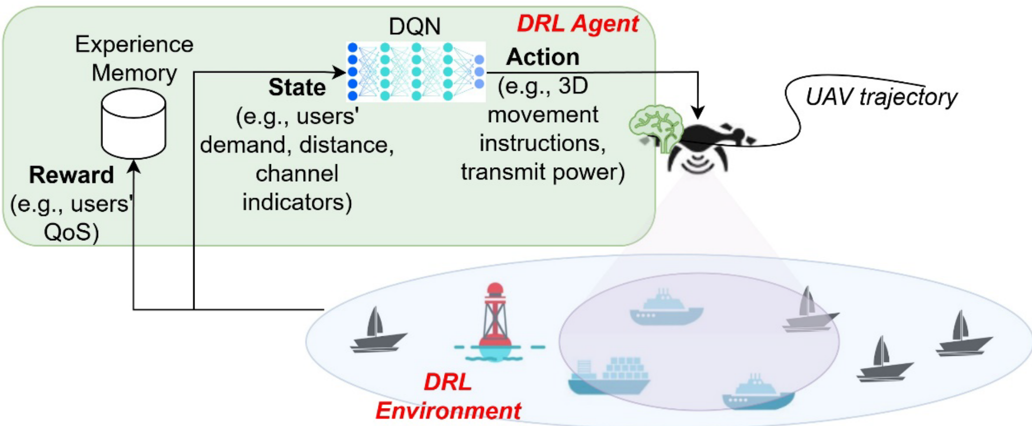

Figure 5. DRL-based optimization of UAV trajectory to maximize sea users' QoS.

4.3. Multi-Client AI/ML Methods

Multi-client methods can be used to combine knowledge across multiple models. Key methods include Ensemble Learning (EL), FL and Transfer Learning [50,62]. EL allows the inference of multiple models for the same input to generate an "average opinion". For instance, the predictions made by different models (e.g., Decision Tree, Linear Regression and Neural Network) for ship's fuel consumption forecasting can be averaged to obtain a more stable global prediction. FL enables distributed devices (e.g., ships, sea BSs, UAVs, control centers) to collaboratively train a shared AI model while keeping their raw data local [62]. Only model updates are exchanged, preserving data

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privacy and reducing bandwidth. This is a critical advantage of FL to ensure privacy, bandwidth efficiency and regulatory compliance. TL allows a model trained in one domain to be reused in another with limited retraining (e.g., a model trained by one ship for route optimization can be used by other ships) [50]. This is useful when training from scratch is not feasible due to cost or limited data. Figure 6 depicts a multi-vessel FL cycle in a single sea area, where different ship-specific local models collaborate to build a global model. In the same example, the global FL model can be transferred through a UAV to a distant sea area, becoming available for inference from other vessels. These techniques enable many MCN-related optimization cases such as:

- **Collaborative diagnostics:** FL can securely enable each vessel to train a local model for fault prediction and share updates to build a robust global model [63].
- **Swarm intelligence-based threat detection:** AUVs and UAVs share model updates through FL to detect environmental hazards or intrusions [5].
- **Decentralized predictive routing:** Ships in a cluster learn shared FL models to predict optimal next-hop links based on their individual experiences [64].
- **Environmental transfer:** Models trained in the Mediterranean on vessel routing can be transferred and adapted to Arctic shipping lanes with a few localized updates.
- **Port-to-ship adaptation:** A model trained on container flow data in a smart port can be transferred and fine-tuned to predict cargo handling efficiency aboard a vessel [65].

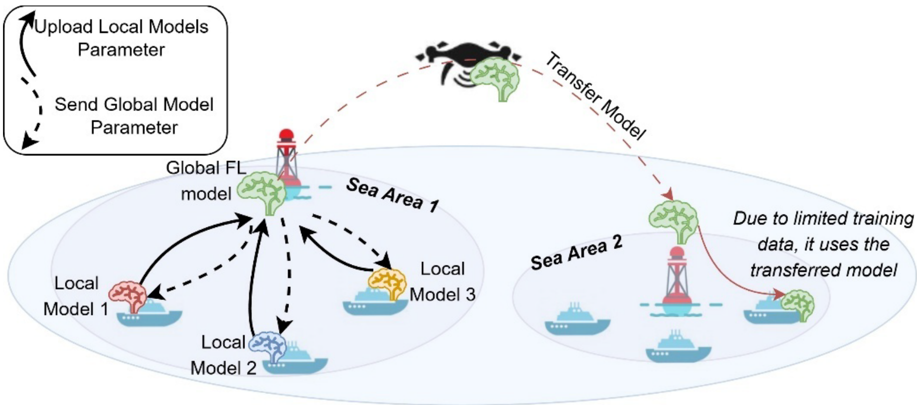

Figure 6. Federated Learning across multiple vessels (sea area 1) and Transfer Learning between distant sea areas (from sea area 1 to sea area 2).

4.4. Generative AI/ML Methods

Generative Adversarial Networks (GANs) are a class of models capable of synthesizing realistic data, including images, signals, or time series for training purposes [66]. They are valuable when collecting real maritime data is costly or unsafe. GANs consist of two neural networks (generator and discriminator) that compete to generate realistic data samples. As shown in Figure 7a, the generator learns to generate fake data, and the discriminator learns to distinguish the generator's fake data from real ones. As training progresses, the generator creates realistic samples, and the discriminator starts to classify fake data as real, leading to the generation of synthetic datasets with realistic statistical properties. In the maritime domain, GANs can be used for:

- **Generation of synthetic sensor data:** Useful for training AI/ML models when collecting real samples (e.g., deep-sea anomaly events) is hard to collect.
- **AIS traffic generation:** For testing routing algorithms or intrusion detection systems without deploying real ships.
- **Creation of training data for rare faults:** GANs can simulate noisy patterns associated with unusual mechanical or communication failures.

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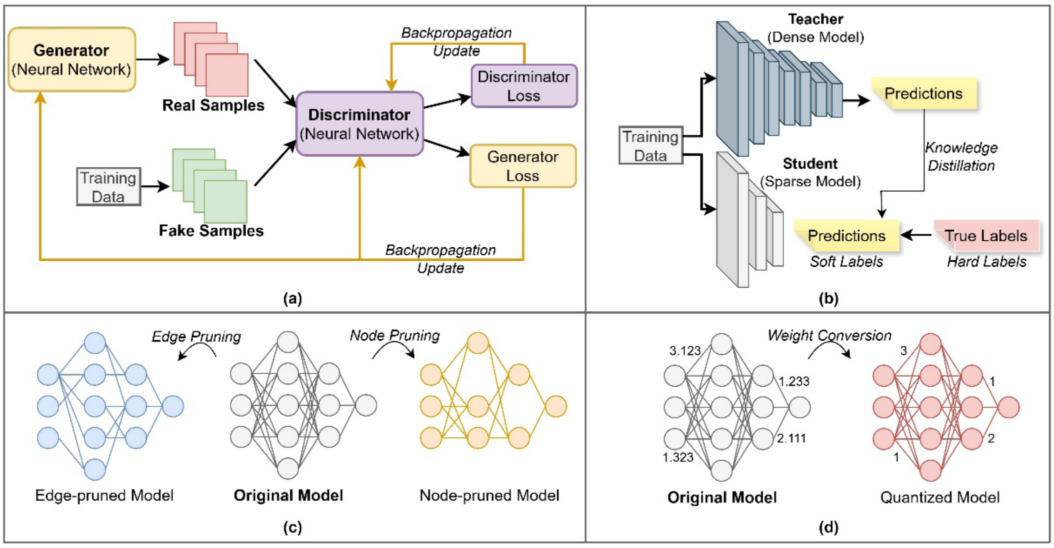

Figure 7. **(a)** Generative Adversarial Network architecture; **(b)** Teacher-Student models for lightweight model creation; **(c)** Model pruning by cutting edges (left) or nodes (right); **(d)** Model quantization via weight rounding for memory-efficient model creation.

4.5. Lightweight AI/ML Methods

When the target predictive function is complex (e.g., multi-factor optimal routing prediction), usually large, dense and computationally-intensive AI/ML models are required to ensure high accuracy. These models can be hosted for inference only in central clouds or distant locations, given that ships or UAVs are equipped with resource-constrained devices. Lightweight AI/ML methods allow complex models ("teachers") that are trained centrally (e.g., cloud-based) to transfer their knowledge to simpler models ("students") [67]. These lightweight models can operate efficiently on ships or buoys with limited compute power, while ensuring adequate performance. Such techniques are known as Teacher-Student Learning and include methods such as Knowledge Distillation [67] (see Figure 7b), Model Pruning [68] (see Figure 7c), or Model Quantization [69] (see Figure 7d). Knowledge distillation involves training a compact “student” model to replicate the behavior of a larger “teacher” model. The Maritime sector may benefit from these methods in the following cases:

- **Lightweight inference at the edge:** Knowledge distillation allows for on-ship diagnostics or onboard object detection by using distilled or pruned models for real-time tasks.
- **Hierarchical decision-making:** Complex teacher models can handle strategic planning, while small-scale student models can operate in real-time at the edge.
- **Model compression:** Using distillation to compress large predictive models (e.g., collision forecasting) for onboard inference without cloud dependence.

The above-mentioned examples are crucial for low-power, bandwidth-limited, or autonomous edge maritime systems.

5. Potential 6G Applications in the Maritime Sector

The unique operational demands of the maritime industry, ranging from long-distance voyages in remote waters to latency-critical port operations, require next-generation communication systems that are intelligent, ultra-reliable, and globally available. In this section, we present five representative 6G-driven maritime use cases, although plenty of use cases and other applications may be considered.

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5.1. AR/VR-Based Fault Diagnosis and Maintenance Support Onboard

Maritime vessels often operate with limited engineering personnel, especially during deep-sea missions. Using 6G-powered AR/VR headsets, onboard crew can perform real-time diagnostics and guided maintenance, assisted remotely by expert technicians onshore or in other ships, as depicted in Figure 8 [70]. These services rely on URLLC and edge-assisted rendering, ensuring immersive interaction with digital twins of onboard systems. The use of digital overlays enables contextual fault visualization, part identification, and even step-by-step repair workflows, all without the need for direct physical supervision [71].

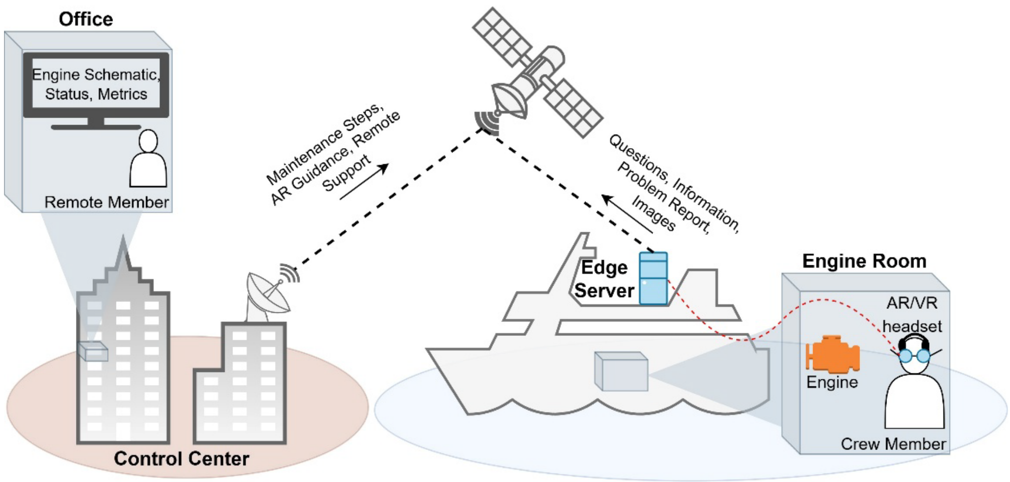

Figure 8. Satellite communication-based remote support in the onboard personnel for fault diagnosis and maintenance guidelines based on AR/VR information.

5.2. Emergency Signal Delivery and Latency-Critical Event Response

In maritime settings, emergency events, such as equipment failure, fire, collision risk, or crew medical emergencies, demand instantaneous and reliable communication with nearby vessels, rescue authorities, or port infrastructure [72]. 6G supports ultra-low-latency, AI-prioritized network slicing, ensuring that emergency signals are delivered even during peak traffic or satellite congestion. Additionally, ISAC can detect abnormal patterns (e.g., abrupt vessel tilting, temperature surges) and trigger autonomous distress alerts with precise location and context-aware metadata.

5.3. Intelligent Fleet Management and Route Optimization

Modern maritime logistics involve dynamic fleet operations where vessels adjust their speed, trajectory, and fuel consumption based on sea conditions, port congestion, and energy efficiency goals [73]. With 6G, AI agents running at the network edge or onboard vessels can continuously optimize routes in real time by integrating data from satellites, HAPs, coastal sensors, and digital twins of maritime traffic. Fleet-wide learning via federated models allows for collaborative planning (e.g., storm avoidance, fuel-efficient paths), while maintaining the privacy of individual operators. Figure 9 illustrates the conceptual schematic of the above-mentioned scenario.

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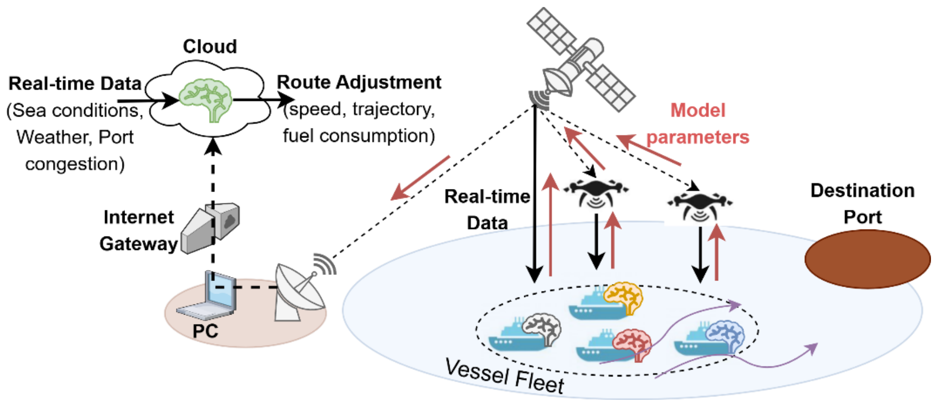

Figure 9. Dynamic Fleet route optimization based on multi-location heterogenous data and fleet-wide Federated Learning. Local models are uploaded to cloud for periodical averaging.

5.4. Just-In-Time Port Arrivals and Smart Port Synchronization

Congestion at ports leads to delays, wasted fuel, and disrupted supply chains. 6G-enabled Just-in-Time (JIT) arrival systems use predictive analytics and ultra-reliable communication to coordinate ship arrivals, berth allocation, cargo handling, and customs processing [74]. Ships adjust their arrival times based on real-time port data, improving throughput and environmental sustainability [75]. Optionally, RIS-aided links, terahertz relays, and MEC platforms at sea BSs or buoys enable high-bandwidth, low-latency connections even several nautical miles from port. The scenario depicted in Figure 9 (fleet route optimization) may be considered for JIT arrival by assuming that routing decisions target to accelerate or delay the ships' movement so as to ensure on-time arrival at port.

5.5. Remote Maritime Surveillance and Border Security

Securing territorial waters and detecting unauthorized activity (e.g., illegal fishing, trafficking) is a top priority for many nations [76]. With 6G, autonomous UAV swarms, connected to LEO satellites and intelligent edge controllers, can perform coordinated surveillance over wide maritime zones. These UAVs share data through multi-hop aerial relaying and use AI-based anomaly detection to flag suspicious patterns in real time, as shown in Figure 10 [77]. RIS elements on buoys and sea BSs can extend detection coverage, while digital twin integration allows mission operators to simulate threats and test response protocols.

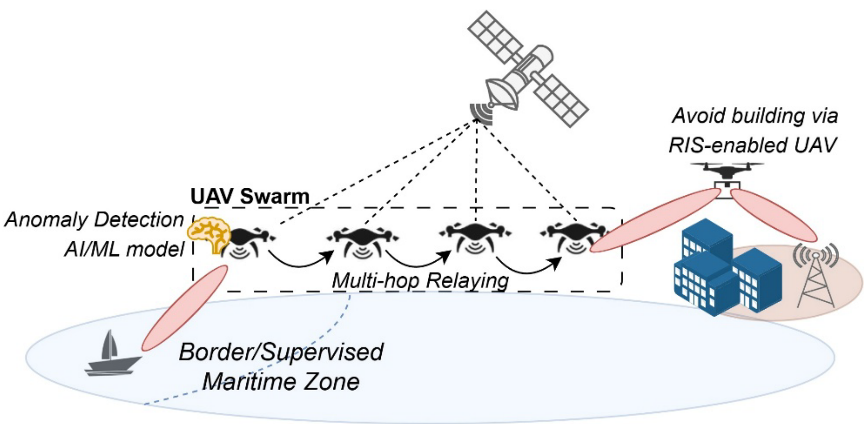

Figure 10. Suspicious activity detection in protected areas through UAV multi-hop relaying towards ground BSs.

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6. Optimization Scenarios for 6G MCNs

As MCNs evolve into highly heterogeneous, AI-driven, and distributed systems under the 6G paradigm, resource allocation and optimization challenges become more complex and critical. This section presents three representative optimization scenarios that provide room for future research, each based on real-world MCN functionality. For each case, we provide a high-level description, mathematical formulation of the core optimization problem, and a discussion of suitable solution approaches, ranging from classical heuristics to advanced learning algorithms.

6.1. Dynamic Spectrum Allocation in Heterogeneous Maritime Environments

In MCNs, multiple communication entities (e.g., ships, UAVs, satellites, buoys) and other mobile nodes often share overlapping radio spectrum resources. The reuse of frequency bands across different communication layers (e.g., UAV-to-ship, ship-to-ship) is essential for achieving high spectral efficiency, especially in spectrum-constrained regions [78]. However, this reuse introduces inter-domain interference, which can significantly degrade overall network performance. Therefore, one of the key challenges is to allocate spectrum resources dynamically across all maritime nodes in a way that maximizes total data throughput while minimizing mutual interference and satisfying individual QoS constraints. Although different assumptions and problem-specific settings may be considered, below we provide the key elements of the mathematical problem formulation for dynamic spectrum access [79]:

Optimization Problem Formulation: If we assume N communication nodes (e.g., ships, UAVs, buoys) drawn from the set $\mathcal{N} = \{1,2,\dots,N\}$ and F available frequency channels selected from the set $\mathcal{F} = \{1,2,\dots,F\}$. A binary variable $x_{i,f}$ can indicate whether node $i \in \mathcal{N}$ occupies frequency channel $f \in \mathcal{F}$. Let also the communication data rate achieved by node i be denoted as R_i (in bps). The data rate R_i typically refers to the achievable Shannon capacity on a wireless channel, assuming a single-user channel (or orthogonal multiple access). A standard formulation is:

$$R_i = B_i \log_2\left(1 + \frac{P_i h_i}{I_i + N_0 B_i}\right) \quad (1)$$

where B_i is the bandwidth allocated to node i (in Hz), P_i is the transmission power of node i (in Watts), h_i is the channel power gain between node i and its serving transmitter, I_i is the total interference received at the node's receiver (Watt), and N_0 is the noise power spectral density (W/Hz) at the receiver. In this optimization model, it can be assumed that channel state information (CSI) is known (which can be realistic if CSI is periodically measured or estimated), then h_i is known. Also, the aggregated interference of node i across its multiple interferers (i.e., nodes transmitting over the same channel) can be derived as:

$$I_i = \sum_{j\in\mathcal{N}, j\neq i} \sum_{f\in\mathcal{F}} x_{i,f} x_{j,f} P_j h_{j,i} \quad (2)$$

where $h_{j,i}$ channel power gain from interferer node j to the wanted node i. Note that, in nearshore, port, or MEC-based settings, the controller may periodically collect CSI and traffic parameters and compute estimated interference level $I_{i,j} = P_j h_{j,i}$ (caused between nodes when they use the same frequency) based on propagation models (e.g., path loss, fading). Thus, in the above formulation, the data rate R_i is derived from the Shannon capacity, while interference $I_{i,j}$ represents the received interference power at node i from node j sharing the same frequency. In centralized or simulation settings, $I_{i,j}$ can be computed from known positions, power levels, and channel models. In distributed or dynamic environments, $I_{i,j}$ may be also approximated or learned through environmental feedback.

Based on the above definition, the optimization objective function can be written as follows:

$$\max_{x_{i,f}} \left(\sum_{i\in\mathcal{N}} R_i - \sum_{i,j\in\mathcal{N}} \sum_{f\in\mathcal{F}} x_{i,f} x_{j,f} I_{ij} \right) \quad (3)$$

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$$\text{s.t. (C1)} \quad \sum_{f \in \mathcal{F}} x_{i,f} \leq 1, \quad \forall i \in \mathcal{N}$$

$$\text{(C2)} \quad R_i \geq R_{min,i}, \quad \forall i \in \mathcal{N}$$

where the goal is to find the channel allocation policy such that to jointly maximize throughput and minimize interference. This optimization function has two competing components, namely (i) the first term rewards configurations that yield higher cumulative data rates across the network and (ii) the second term penalizes total interference generated by nodes sharing the same frequency channel, especially when they are within interference range. The goal is to find a balance between maximizing network throughput and reducing mutual interference, which is a typical utility-minus-cost structure used in resource allocation problems. The solution should also comply with constraint (C1), implying that each node can be assigned at most one frequency channel, and (C2), reflecting that each node must meet a minimum required data rate, which may depend on its role (e.g., control UAVs may need higher guarantees than monitoring sensors).

Potential Solution Approaches: To find a (sub)optimal solution to problem (3), several iterative, heuristic or AI-based algorithms can be used. Below, we analyze two widely-used approaches to tackle this problem:

1. ***Graph Coloring and Greedy Heuristics:*** This approach models the network as a conflict graph, where nodes represent transmitters and edges represent potential interference (i.e., two nodes within range that cannot use the same channel) [80]. The graph coloring problem assigns frequencies (colors) to nodes so that adjacent nodes (interfering nodes) receive different or orthogonal channels. One approach may be Greedy Coloring, which sorts nodes by degree (number of neighbors) and, then, assign to every node the first available frequency that doesn't conflict [81]. Another option could be the Weighted Heuristics, in which we use metrics such as required throughput or signal strength to prioritize channel assignment. Key advantages of both are (i) their fast, interpretable, and easy impementation, and (ii) their suitability for near-real-time decisions in static or slowly varying maritime environments [80,81].
2. ***RL-based Solution:*** In dynamic settings with mobility (UAVs, ships) and time-varying interference, RL enables nodes to learn optimal spectrum usage policies over time [78]. In this framework, each communication node (e.g., a ship or UAV) can be seen as an agent that observes a state and performs actions, which lead to a predefined reward. The state vector may describe the local channel occupancy, recent interference levels, and QoS status of the node. The agent, upon reading the state, selects a frequency channel from the set $\mathcal{F}$. Then, the environment returns a reward to reflect whether the action was beneficial or not. This rewarding function can combine the achieved throughput (positive reward) and experienced interference or dropped packets (penalty). For large state-action dimensionality, DRL method can be considered, where a neural network estimates the Q-values for each state-action pair [78]. During the training, the goal is to maximize the accumulated long-term reward. As a result, upon a series of training episodes, the agent converges to an optimal solution according to which the best frequency channel is selected for any given state [79].

6.2. Energy-Efficient Communication for UAVs and AUVs

UAVs and AUVs play critical roles in surveillance, data relaying, monitoring, and exploration. However, both UAVs and AUVs are subject to strict energy constraints, stemming from limited onboard battery capacity and the high cost of recharging or recovery, especially in long-duration, remote, or autonomous missions [82]. Consequently, there is a need to design communication strategies that minimize energy consumption while ensuring that data transmission requirements are

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met [83,84]. These strategies must intelligently adjust transmission power, data rate, or active/sleep scheduling, often under uncertain and dynamic network conditions.

Optimization Problem Formulation: Let $\mathcal{N}$ be the set of UAVs and AUVs, each needing to transmit a certain amount of data to a destination node (e.g., a base station, a satellite, or another vehicle). For each node $i \in \mathcal{N}$, we can define: P_i as the transmission power of node i (decision variable); $R_i(P_i)$ as the data rate of node i as a function of P_i; E_i as the energy consumed from node i (typically proportional to transmission power); $R_{min,i}$ as the minimum required rate (QoS constraint); and $P_{max,i}$ as maximum allowed transmit power. Thus, we aim to minimize the total communication energy while satisfying rate and power constraints, as reflected in the following problem:

$$\min_{P_i} \sum_{i\in\mathcal{N}} \frac{P_i}{\eta_i}$$

$$\text{s.t. (C1)} \quad R_i(P_i) = B_i \log_2\left(1 + \frac{h_i P_i}{N_0 B_i}\right) \geq R_{min,i}, \quad \forall i \in \mathcal{N} \tag{4}$$

$$\text{(C2)} \quad 0 \leq P_i \leq P_{max,i}, \quad \forall i \in \mathcal{N}$$

where $\eta_i \in (0,1]$ is the power amplifier efficiency of node i. The objective function represents the energy required for transmission over a given duration (e.g., normalized to 1 time unit for simplicity). The solution to this problem regulates the transmitting power of nodes so as to ensure minimized energy consumption, while respecting the constraints (C1) and (C2). The first constraint guarantees a minimum data rate QoS assuming that B_i is the bandwidth for transmission, h_i channel gain (may vary based on altitude, sea clutter, or mobility) and N_0 noise power spectral density. The second constraint ensures that power levels are non-negative and upper-bounded by the nodes' power budget.

Potential Solution Approaches: Problem (4) can be solved by different optimization algorithms to find the power allocation that minimizes nodes' energy consumption. Below, we summarize some of the potential solvers that can be used to tackle problem (4):

1. ***Convex Optimization with Dual Decomposition*** [85]**:** When the data rate function $R_i(P_i)$ is convex and differentiable (as in log-based Shannon capacity models), the optimization problem is convex and can be solved using Lagrangian duality [86], dual decomposition, or Water-filling algorithm (in multi-channel cases) [87]. Lagrangian duality introduces Lagrange multipliers for the QoS constraints and solve via the Karush–Kuhn–Tucker (KKT) conditions [86]. In dual decomposition methods, we separate the global problem into per-node subproblems and solve them in parallel. Finally, multi-channel Water-filling solutions can be used to allocate more power to better links, while ensuring the total energy is minimized. These approaches can be easily implemented and compared between each other, and they are applicable in centralized MCNs (such as when a Sea BS controls a group of AUVs/UAVs).

2. ***DRL for Distributed Energy Optimization:*** When system dynamics are non-stationary or partially observable (e.g., unknown channel gains, time-varying loads, or node failures), DRL offers a powerful model-free solution [88]. Each UAV/AUV can be modeled as an agent that interacts with its environment. The state observed is each DRL episode can include local channel conditions, residual battery level, past transmission outcomes, whereas the action taken by each agent is the selection of transmission power level (or sleep/awake state) [89]. The received reward for a given action can be the negative consumed energy, penalized if QoS is violated, as reflected in the following formula:

$$r_t = -\frac{P_t}{\eta} + \lambda \cdot I_{\{R_t \geq R_{min}\}} \tag{5}$$

where the reward r_t collected at time t is maximized when the power allocation P_t is minimum (first term). The second term reflects an extra constant reward λ that is given when the QoS is satisfied (i.e., $R_t \geq R_{min}$), as defined by the indicator function $I_{\{R_t \geq R_{min}\}}$ which equals to 1 when the condition is true (otherwise it is 0). For large-scale systems, DRL or Proximal Policy Optimization (PPO) agents [90] can be used to learn power allocation strategies that achieve the lowest possible energy consumption with satisfied QoS.

6.3. Task Offloading to Edge Nodes in MCNs

Many maritime nodes such as ships, UAVs, AUVs, and buoys are equipped with onboard sensors and computing units that continuously generate data (e.g., from video feeds, radar, sonar, or environmental monitoring). However, processing these data-intensive workloads locally can lead to high energy consumption, increased latency, or degraded performance, especially in resource-constrained platforms. 6G introduces a continuum of edge, aerial, and satellite computing nodes, enabling these maritime devices to offload computation to more powerful or better-situated processing units [34,91,92]. The goal is to optimize the offloading decision such that total latency and energy consumption are minimized, while respecting network and compute constraints.

Optimization Problem Formulation: Let $\mathcal{U}$ denote the set of task-generating nodes (e.g., ships), and $\mathcal{E}$ denote the set of candidate computing edge nodes (e.g., UAVs, satellites, Sea BSs). We consider a per-node decision $D_i = 1$ when the task is to be locally computed, whereas $D_i = 0$ when the task is to be offloaded. If offloading is decided, each task offloading decision can is represented by $x_{i,n} \in \{0,1\}$, a binary variable that is $x_{i,n} = 1$ when node $i \in \mathcal{U}$ offloads its task to edge node $n \in \mathcal{E}$ (otherwise 0). When the task is locally processed in node i, we denote the processing delay as T_i^{local} and the energy consumed as E_i^{local}. With known number of CPU cycles c_i needed for task i and local CPU frequency f_i (in Hz) of node i, the time to compute the task locally is [34,91]:

$$T_i^{\text{local}} = \frac{c_i}{f_i} \tag{6}$$

Similarly, when the task of node i is offloaded to edge node n, we let $T_{i,n}^{offload}$ be the offloading delay and $E_{i,n}^{offload}$ be the respective energy consumption. The computational capacity of edge node n is C_n (in Hz). Note that, $T_{i,n}^{offload}$ is the total delay to transmit the task towards node n (denoted as $T_{i,n}^{tx}$), plus the delay to process it at node n (denoted as $T_{i,n}^{proc}$), which can be written as:

$$T_{i,n}^{\text{offload}} = T_{i,n}^{\text{tx}} + T_{i,n}^{\text{proc}} \tag{7}$$

The goal is to minimize the total weighted cost of delay and energy, across all tasks and offloading options, as reflected by the optimization problem:

$$\begin{aligned} \min_{D_i, x_{i,n}} \sum_{i \in \mathcal{U}} \Bigg(& D_i\big(\alpha T_i^{\text{local}} + \beta E_i^{\text{local}}\big) \\ & + (1 - D_i) \sum_{n \in \mathcal{E}} x_{i,n}\big(\alpha T_{i,n}^{\text{offload}} + \beta E_i^{\text{offload}}\big) \Bigg) \\ \text{s.t. (C1)} \quad & D_i + \sum_{n \in \mathcal{E}} x_{i,n} \leq 1, \quad \forall i \in \mathcal{U} \\ \text{(C2)} \quad & \sum_{i \in \mathcal{U}} x_{i,n} \cdot c_i \leq C_n, \quad \forall n \in \mathcal{E} \\ \text{(C3)} \quad & x_{i,n} \cdot \frac{d_i}{B_{i,n}} \leq T_{max}, \quad \forall (i,n) \in \mathcal{U} \times \mathcal{E} \end{aligned} \tag{8}$$

where α and β are application-specific constant weighting factors (e.g., emphasizing latency over energy or vice versa). Evidently, the objective function represents a weighted optimization of delay and energy consumption for both local computation (first term) and edge computation upon offloading (second term). The goal is to find the decision variables $(D_i, x_{i,n})$ that minimize the overall delay and power consumption, while respecting constraints (C1)-(C3). The first constraint (C1) ensures that each task is executed to at most 1 nodes. The second constraint (C2) guarantees that

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the total processing demand of all tasks offloaded to edge node n n does not exceed its computational budget C_n. Finally, the third (C3) guarantees that the task size d_i (in bits) transmitted to node n over wireless link with bandwidth $B_{i,n}$ (in bps) respects a maximum latency limit T_{max} (i.e., if this constraint is disrespected, it means that offloading is not feasible for that task-edge pair).

Potential Solution Approaches: Multiple solvers can be used to provide a solution to problem (8). Below, we describe the major among them:

1. ***Mixed Integer Linear Programming (MILP):*** The offloading problem can be formulated as a MILP when all latency and energy models are linearized [19,93]. MILP solvers (e.g., CPLEX, Gurobi [19]) can produce optimal solutions for small- to medium-scale networks. However, this approach is computationally intensive for large dynamic MCNs, and not scalable when task arrival is continuous or unpredictable.
2. ***Multi-Agent Reinforcement Learning (MARL):*** In a distributed MCN setting, task offloading can be modeled as a multi-agent RL problem, where each maritime node (ship, UAV, buoy) is an agent deciding whether to offload and to which edge server [91]. In the formulation of MARL, the agents' state can include local task queue, channel quality, residual energy, and/or nearby edge availability. The agents may select an edge node for offloading or choose local execution (i.e., action). The reward collected at each step can be defined as in the optimization function in problem (8) (i.e., weighted delay-energy cost), possibly by further penalizing the agents for task drops [34].

Note that, although this section provided the formulation basis of three different optimization methods, there might be also other emerging resource allocation problems in 6G MCNs, including UAV trajectory planning for coverage optimization [94], RIS and beamforming optimization [95], FL across heterogeneous maritime devices [50,62] and latency-constrained multi-hop routing [96].

7. Conclusions

This paper presented a comprehensive review of the emerging role of 6G technologies in transforming MCNs. After highlighting the limitations of existing maritime communication systems, a reference architecture for heterogeneous MCNs was proposed, integrating terrestrial, aerial, satellite, sea-surface and underwater components to support seamless and resilient connectivity. The core features of 6G were then examined, including THz communications, RIS, ISAC, AI-native network design, and UAV-augmented coverage. It was also assessed how these innovations address key maritime challenges. Several representative maritime use cases were also presented. Furthermore, we proposed and mathematically formulated key optimization scenarios for spectrum allocation, energy-efficient UAV communications, and task offloading, reporting some potential solvers to these problems.

Future work may focus on implementing real-time learning models in harsh maritime environments, integrating digital twins for predictive analytics and fleet simulation. Validating proposed solutions in multi-agent simulations or sea-based testbeds would be also critical. Overall, this paper outlines a new generation of intelligent, adaptive, and autonomous MCNs, highlighting the potential role of AI and open room for further research.

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Abbreviations

The following abbreviations are used in this manuscript:

4G	Fourth Generation
5G	Fifth Generation
5G NR	5G New Radio
6G	Sixth Generation
A2S	Air-to-Sea
AI	Artificial Intelligence
AR	Augmented Reality
AUV	Autonomous Underwater Vehicle
BS	Base Station
DRL	Deep Reinforcement Learning
eMBB	Enhanced Mobile Broadband
FL	Federated Learning
HAP	High-Altitude Platform
IRS	Intelligent Reflecting Surface
ISAC	Integrated Sensing and Communication
ISM	Industrial, Scientific, and Medical
LEO	Low Earth Orbit
LoS	Line of Sight
LTE	Long-Term Evolution (4G)
MANET	Maritime Ad Hoc Networks
MCN	Maritime Communication Network
MEC	Mobile Edge Computing
MIMO	Multiple-Input-Multiple-Output
mMTC	Massive Machine Type Communications
mmWave	Millimeter Wave
ML	Machine Learning
NLoS	Non-Line-of-Sight
ANN	Artificial Neural Network
NOMA	Non-Orthogonal Multiple Access
PPO	Proximal Policy Optimization
QoS	Quality of Service
RIS	Reconfigurable Intelligent Surfaces
RL	Reinforcement Learning
S2S	Ship-to-Ship
S2Sh	Ship-to-Shore

Sat-BS	Satellite Base Station
SemiSL	Semi-Supervised Learning
SL	Supervised Learning
UAV	Unmanned Aerial Vehicle
UHF	Ultra-High Frequency
UL	Unsupervised Learning
URLLC	Ultra Reliable Low Latency Communications
VHF	Very High Frequency
VR	Virtual Reality
XR	Extended Reality

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