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A Survey on UAV-Aided Maritime Communications: Deployment Considerations, Applications, and Future Challenges

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Maritime activities represent a major domain of economic growth with several emerging maritime Internet of Things use cases, such as smart ports, autonomous navigation, and ocean monitoring systems. The major enabler for this exciting ecosystem is the provision of broadband, low-delay, and reliable wireless coverage to the ever-increasing number of vessels, buoys, platforms, sensors, and actuators. Towards this end, the integration of unmanned aerial vehicles (UAVs) in maritime communications introduces an aerial dimension to wireless connectivity going above and beyond current deployments, which are mainly relying on shore-based base stations with limited coverage and satellite links with high latency. Considering the potential of UAV-aided wireless communications, this survey presents the state-of-the-art in UAV-aided maritime communications, which, in general, are based on both conventional optimization and machine-learning-aided approaches. More specifically, relevant UAV-based network architectures are discussed together with the role of their building blocks. Then, physical-layer, resource management, and cloud/edge computing and caching UAV-aided solutions in maritime environments are discussed and grouped based on their performance targets. Moreover, as UAVs are characterized by flexible deployment with high re-positioning capabilities, studies on UAV trajectory optimization for maritime applications are thoroughly discussed. In addition, aiming at shedding light on the current status of real-world deployments, experimental studies on UAV-aided maritime communications are presented and implementation details are given. Finally, several important open issues in the area of UAV-aided maritime communications are given, related to the integration of sixth generation (6G) advancements. These future challenges include physical-layer aspects, non-orthogonal multiple access schemes, radical learning paradigms for swarms of UAVs and unmanned surface and underwater vehicles, as well as UAV-aided edge computing and caching.

***Index Terms*—Maritime communications, maritime Internet of Things (IoT), sixth-generation (6G) mobile communication networks, space-air-ground-sea integrated networks, underwater IoT, unmanned aerial vehicles (UAVs).**

I. INTRODUCTION

In the past decades, wireless networks have been evolving towards supporting users services, which are located in urban environments, while the fourth and fifth generations (4G and 5G) of mobile communications have put special emphasis in the coexistence of mobile users and Internet-of-Things (IoT) devices [1]–[4]. Unfortunately, most network architectures and communication techniques were designed for land-based communications, while the maritime domain has been largely neglected from this revolution. As a result it is mainly based on the satellite segment, with the known issues of high-latency and low-data rates [5]. Considering that the vast majority of trade relies on maritime transportation, while the interest for a wide range of maritime activities, such as ocean exploration for natural resources and pollution monitoring, has spiked, a radical shift to maritime communications is needed [6]. In this context, the rise of unmanned aerial vehicles (UAVs) and their integration in wireless networks provides a viable means for achieving broadband coverage at sea [7]–[9]. UAVs are capable of flexibly providing radio-resources depending on the Quality-of-Service (QoS) requirements of applications and can operate autonomously in a distributed manner, ensuring high reliability and low-latency.

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Thus, it is critical to efficiently integrate UAVs in maritime environments in order to achieve ubiquitous connectivity and support maritime applications on the water surface and underwater [10]. In this survey, the role of UAVs in facilitating maritime communication networks (MCNs) is presented and current solutions are given in detail. For this purpose, relevant communication techniques are discussed and categorized according to network layer and performance target. Moreover, several network architecture propositions, comprising UAVs, satellites, terrestrial and heterogeneous maritime network nodes are shown and various open issues stemming from this important research area are given in detail, targeting to stimulate further interest in UAV-aided maritime communications.

A. Maritime communications

MCNs aim at supporting applications related among others, to trade, ocean exploration, pollution monitoring, marine tourism, and search and rescue (SAR) operations [11], [12]. Such an ecosystem relies on a heterogeneous mix of vessels, buoys, platforms, unmanned surface vehicles (USVs) and unmanned underwater vehicles (UUVs), sensors, and actuators [8]. In addition, maritime services are characterized by varying QoS types, since, for example, crew and passengers on-board cruise ships might be interested in broadband connectivity, SAR operations entail the transmission of real-time video, while IoT services in smart maritime environments and intelligent transportation systems are based on Ultra-reliable and ultra-low latency (URLLC) [13], [14].

The current paradigm for providing coverage to maritime activities depends on shore-based base stations (BSs) and satel-

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TABLE I
LIST OF SURVEYS PRESENTING MCN SOLUTIONS.

Reference	Short summary	Contributions
Wei et al. [15]	A survey on hybrid satellite-terrestrial networks for maritime IoT applications	- Maritime communications challenges, related to meteorological and geographical characteristics and heterogeneous service requirements are discussed - Hybrid-satellite terrestrial technologies for high transmission efficiency, wide network coverage, and maritime-specific services are discussed - Very few works related to UAV-aided maritime communications are included
Jahanbakht et al. [10]	A survey on the synergy among the Internet of Underwater Things (IoUT) and big marine data analytics	- A thorough overview of IoUT network architectures, communication techniques and state-of-the-art research challenges is presented - The role of big data analytics and machine learning for IoUT applications is given and relevant frameworks and platforms are discussed - UAV-based solutions and related aspects are missing from the survey and the focus is on underwater communications and applications
Alqurashi et al. [13]	A survey on enabling technologies, opportunities, and challenges of maritime communications	- Focus on physical-layer techniques, channel modelling and RRM for maritime communications - Presentation of emerging MCN use cases and open challenges related to THz and visible light communications and data-driven optimization - Very few works on UAV-aided maritime communications are included
This survey	A survey emphasizing on the integration of UAVs for supporting the operation of maritime communication networks	- UAV-aided maritime network architectures and the role of the heterogeneous network nodes are presented - Depending on the network layer that the communication techniques operate, UAV-aided MCN solutions are categorized and critically evaluated - UAV-aided maritime communications open issues, ranging from the physical-layer up to cloud/edge architectures and ML integration are discussed

lite constellations. Unfortunately, such maritime networking architectures are not capable of supporting the increasing number of vessels, USVs, UUVs, sensors and emerging maritime applications, due to low data rates, insufficient spectrum, high communication delays, and unreliable connectivity. Although there have been industrial initiatives on both terrestrial and satellite segments, with broadband satellite coverage and long-distance shore-to-vessel communications using cellular standards [16]–[18], further research on developing flexible and intelligent maritime networks is required. Towards this end, exploiting aerial nodes, as envisioned in various 6G network architectures can mitigate the impact of geographical characteristics on path-loss, reduce communication delays, enhance communication reliability through additional wireless paths, offer dynamic resource provisioning, in terms of radio-access, caching and computing, and support maritime surveillance and search and rescue operations.

B. UAV-aided wireless networks

6G networks are envisioned to support novel network architecture paradigms, encompassing moving nodes for dynamic resource provisioning and increased network resiliency [19], [20]. In this context, the integration of UAVs to complement terrestrial and satellite networks has been investigated in various recent works [8], [21], [22]. UAV-aided networks offer extended coverage in remote and rural settings, quick recovery after disasters and emergency situations, ubiquitous communications in flash crowd traffic demands, enabling various IoT use cases, such as precision agriculture and fleet management [14], [23]. At the same time, there exist various challenges that must be addressed to efficiently integrated UAVs in 6G wireless networks. Such challenges include the co-existence with ground users on the sub-6 GHz spectrum where non-orthogonal multiple access techniques are needed for mass connectivity, the exploitation of mmWave and THz bands while combating higher power consumption and sensitivity to blockage and vibrations, the integration with machine learning (ML) to solve complex communication and network processes, including channel modeling, power control, UAV swarm coordination and trajectory optimization, the use of UAVs with active/passive intelligent reflecting surface (IRS) design and finally, tackling energy-related issues with wireless power transfer for flight time maximization and timely UAV deployment to replace nodes that must re-charge their batteries [24], [25].

In maritime settings, the use of UAVs for satisfying heterogeneous maritime services, requiring broadband connectivity or URLLC for IoT has attracted significant interest in recent years [26]. More specifically, UAVs can be flexibly deployed and assume the role of wireless relays, enabling multi-hop communication between ground BSs and sea vessels. In the case of underwater IoT, UAVs can greatly facilitate data collection by cooperating with USVs and UUVs, enhancing the capabilities of ocean monitoring systems [27]. Meanwhile, during SAR operations, UAVs can provide high capacity line-of-sight (LoS) links in order to facilitate the transmission of real-time video data among the participating vessels and ground stations [28]. An inherent characteristic of UAVs is that energy-efficient communications and trajectory optimization algorithms have to be put in place, while recent advancements in wireless power transfer (WPT) can offer further gains towards extending their flight time. In general, the maritime communication applications that are supported by UAVs, can be categorized as follows:

- Improvement of the maritime SAR operations by offering better coverage, on-demand network deployment, and

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high mobility capabilities, while high-altitude platforms (HAPs) may offer extended coverage radius;

- Data relaying to/from the underwater or surface segments for maritime IoT purposes as well as increased probability for obtaining LoS propagation condition with the base station in various intelligent transportation scenarios;
- Maritime surveillance missions, in which the aim is to patrol a specific region of interest with minimum fuel consumption [29].

These applications cannot efficiently be supported by all types of UAVs. Here, it should be noted that the two main categories of UAVs are the fixed wing and the rotary wing. Fixed wing UAVs are characterized by higher speed, less power consumption that allows them to flight for almost 16 hours, making them useful for long distance missions. However, there exist some issues regarding their applicability since taking off and landing is not an easy task in maritime environments, while they cannot be used for hovering applications. Therefore, this type of UAVs are more appropriate to be used for SAR and security-based surveillance applications. On the other hand, multi rotor UAVs may exploit their greater control over the position and employed in maritime IoT communication scenarios as well as for intelligent transportation communication purposes.

C. Contributions

In recent years, the interest in maritime activities has increased and currently deployed communication infrastructure cannot cope with the requirements of emerging use cases [13], [15]. In this context, UAV-aided solutions represent a radical paradigm shift that complements terrestrial and satellite segments, bringing several unique advantages in terms of deployment flexibility, as well as path-loss and delay reduction. Taking into consideration the potential of integrating UAV in maritime networks, this survey provides a thorough overview of relevant solutions and categorizes them according to the network layer issues and performance target that they address. In greater detail, our contributions are as follows:

- The current status in maritime network architectures is presented, and the integration and role of UAVs is discussed. Also, details on the relevant building blocks are given.
- The physical-layer, resource management, and cloud/edge UAV-aided algorithms for maritime communications are categorized based on their performance targets. Also, recent advancements in UAV trajectory optimization for maritime applications are thoroughly discussed.
- Then, aiming at shedding light on the current status of real-world deployments, experimental studies on UAV-aided maritime communications are presented and implementation details are given.
- Several open issues are highlighted, including IRS-aided communications, non-orthogonal multiple access (NOMA), swarm intelligence for UAVs, USVs and UUVs, and UAV flight time maximization through WPT.

Table I summarizes the contributions of surveys in the field of maritime communications and maritime IoT and their emphasis on UAV integration issues is highlighted. Starting with the survey by Wei *et al.* [15], the authors focus on hybrid-satellite network architectures towards supporting the requirements of maritime IoT. Details on maritime communications challenges are discussed, related to environmental and geographical characteristics, and state-of-the-art solution are categorized according to their goal, i.e., improving the transmission efficiency, ensuring wide coverage and guaranteeing maritime service QoS. However, this survey only includes very few studies on UAV-aided maritime communications. Then, the survey by Jahanbakht *et al.* [10] provides a comprehensive overview and tutorial on the synthesis of IoUT and big marine data analytics. Several IoUT architectures are presented, and details on the interplay among IoUT and machine-learning-aided optimization are provided. However, this survey significantly differs to the one presented in this paper, as the state-of-the-art in UAV-aided maritime networks is completely absent. Another recent survey by Alqurashi *et al.* gives an overview of maritime communications issues and focuses on physical-layer aspects, current developments in channel models and radio-resource management (RRM) algorithms. Moreover, interesting maritime use cases are discussed, highlighting the research potential in this area. Nonetheless, UAV-based solutions are not discussed in the survey, thus leaving a gap in the literature that this work aims to fill.

D. Structure

The structure of this survey is as follows. First, Section II presents the state-of-the-art in architecture designs for UAV-aided maritime network and provides details on their components. Then, Section III includes works focusing on physical-layer issues of UAV-aided maritime communications. Resource management and multiple access aspects are discussed in Section IV, while Section V focuses on the integration of cloud/edge computing and caching for improving the performance of UAV-aided maritime applications. Subsequently, optimal UAV trajectory design in maritime environments is the topic of Section VI and experimental implementations of UAV-aided maritime topologies are discussed in Section VII. Moreover, several important open issues in the area of UAV-aided maritime communications are given in Section VIII. Finally, conclusions are given in Section IX. Overall, the structure of this survey is shown in Fig. 1, while Table II includes the list of acronyms being used throughout this survey.

II. UAV-Aided Maritime Network Architecture

Maritime activities rely on heterogeneous network topologies, where numerous UUVs, USVs, sea vessels, buoys, platforms, and sensors cooperate with UAVs and satellites to enable reliable communications in highly mobile and volatile environments. An illustrative UAV-aided maritime communications architecture is depicted in Fig. I-D. Below, the main architectural segments presented in that figure will be analyzed, as well as the different communication techniques adopted and the various performance targets assumed.

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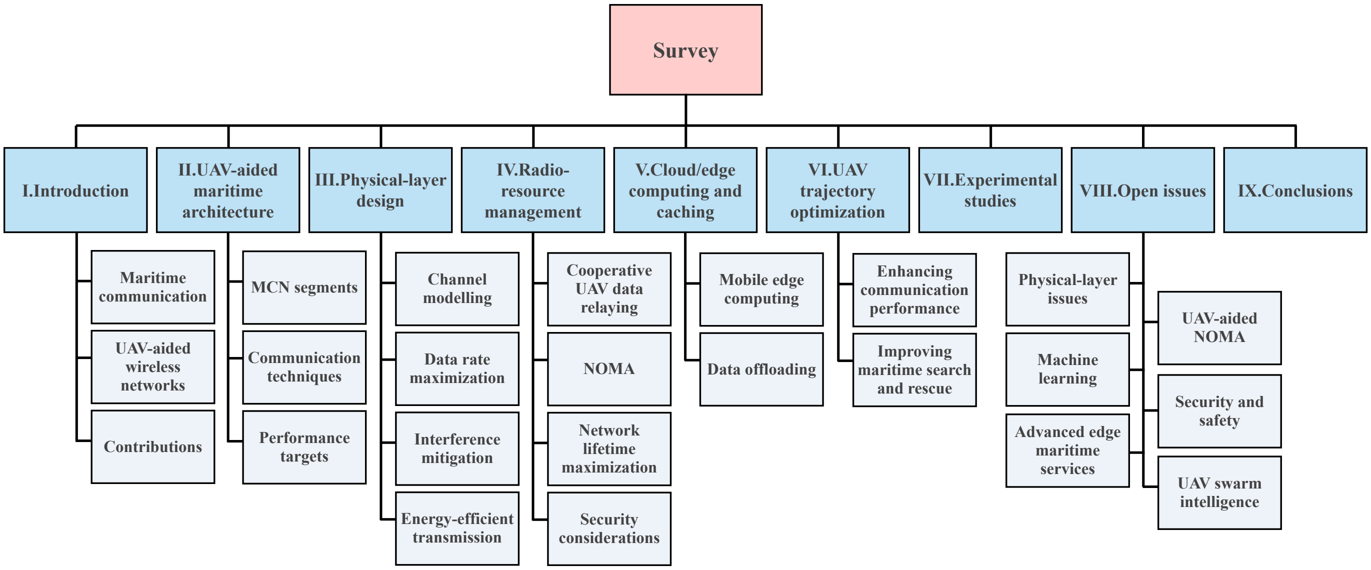

Fig. 1. Survey structure.

TABLE II
LIST OF ACRONYMS

Acronym	Definition	Acronym	Definition	Acronym	Definition
BER	Bit error rate	BS	Base station	CCI	co-channel interference
DCGAN	Deep convolutional generative adversarial network	D2D	Device-to-device	DDPG	Deep deterministic policy gradient
DRL	Deep reinforcement learning	EE	Energy efficiency	FDTD	Finite difference domain method
FL	Federated learning	FSO	Free space optics	GEO	Geostationary earth orbit
HAP	High altitude platforms	IoT	Internet-of-Things	IoUT	Internet of underwater things
IRS	Intelligent reflecting surfaces	LEO	Light emitting diode	LEO	Low Earth orbit
LMS	Least mean square	LoS	Line of sight	LSTM	Long-short-term memory
LTE	Long term evolution	MCN	Maritime communication network	MDP	Markov decision process
MEC	Mobile edge computing	MIMO	Multiple-input multiple-output	mMIMO	Massive MIMO
ML	Machine learning	NLoS	Non-line-of-sight	NOMA	Non-orthogonal multiple access
OMA	Orthogonal multiple access	OMN	Ocean monitoring	PLS	Physical-layer security
PSO	Particle swarm optimization	QoS	Quality-of-Service	RAN	Radio access network
RF	Radio frequency	RL	Reinforcement learning	RRM	Radio resource management
SAR	Search and rescue	SCA	Successive convex optimization	SE	Spectral efficiency
SN	Sink node	SNR	Signal-to-noise ratio	TBS	Terrestrial base station
TDMA	Time division multiple access	UAV	Unmanned aerial vehicle	USN	Underwater sensor network
USV	Unmanned surface vehicle	UUV	Unmanned underwater vehicles	URLLC	Ultra-reliable and ultra-low latency
VHF	Very high frequency	VLC	Visible light communication	WPT	Wireless power transfer

A. MCN segments

As it can be observed in Fig. I-D, four main segments can be identified in an MCN architecture. More specifically, a maritime segment involving underwater and surface activities, a shore segment, an aerial segment and a space segment [30].

1) Maritime segment

Here, the edge nodes of the MCN are located, being responsible for surface and underwater data acquisition, cooperative relaying with multiple modes of communications, and edge computing tasks.

Underwater: In an MCN, the underwater segment includes sensor nodes, underwater buoys and UUVs, being responsible for marine data acquisition and exchange that is forwarded to other MCN nodes, such as UUVs, ships or UAVs. As electromagnetic waves are subjected to high attenuation in seawater when data must be transmitted to longer distances, the nodes of the underwater segment rely on acoustic signals.

Sea surface: On the sea surface, ships, USVs, and buoys reside, communicating to support applications related, among others, to intelligent transportation, environmental observation, data relaying from/to the underwater segment, and maritime SAR. Recently, the introduction of extended coverage giant cells, in the form of seaborne floating towers, being semi-submersible steel reinforced concrete platforms has been pro-

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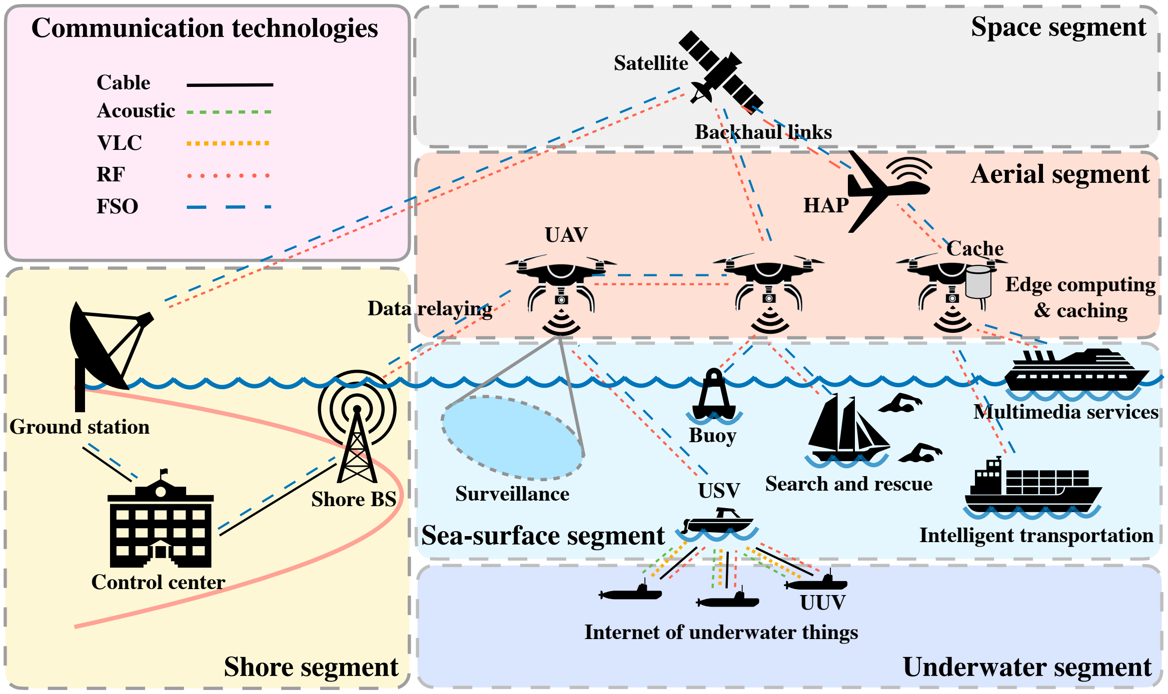

Fig. 2. An illustrative UAV-aided maritime communications architecture.

posed [11].

2) Shore segment

The shore segment hosts BSs that provide coverage to nearby maritime nodes and UAVs, employing cellular standards. Furthermore, on the ground stations communicating with the space segment are present, allowing the transmission of data within the broader MCN.

3) Aerial segment

The existence of shore BS and satellites provides wide coverage to maritime activities but is insufficient to support the QoS of service types that require broadband connectivity or URLLC [31]. Towards this end, UAV-aided MCNs have emerged where a flexible aerial segment allows the dynamic provisioning of radio-resources to remote areas, low-latency compared to satellite links, and high reliability with multi-hop transmissions and diverse wireless paths [32]. Fig. I-D depicts various maritime applications that are supported by UAVs, including data relaying to/from the underwater and surface segments for maritime IoT purposes, support for maritime SAR and surveillance, as well as communication with sea vessels desiring intelligent transportation and multimedia service provisioning. In addition, to UAVs, the aerial segment can employ HAPs mainly residing at the stratosphere.

4) Space segment

The space segment encompasses different satellite systems, in the sense of geostationary earth orbit (GEO)-based INMARSAT and low-earth orbit (LEO) constellations, such as Starlink. The main responsibilities of the space segment include its use as a back-up when the shore BSs and the aerial segment fail to provide coverage to maritime nodes and backhauling/fronthauling in order to enable data availability across the whole MCN structure.

B. Communication Technologies

Stemming from the heterogeneity of MCN segments, different communication technologies are usually employed in order for the MCN to adjust to the various environmental and propagation characteristics. The vast majority of communication solutions are wireless and only in some underwater topologies, communication relies on wired connections. As a result, below we focus on the various wireless communication technologies for MCNs.

1) Radio frequency (RF) communications

In conventional maritime communication systems, RF-based transmissions operate on the very high frequency band (VHF) between 156–174 MHz and provide radio services and SAR support. Nonetheless, the provision of broadband services and maritime IoT applications will use cellular and Wi-Fi bands that can cope with high data rate and low-latency requirements, exploiting the re-position capabilities of UAVs for improved wireless connectivity [33]–[35] and direct communication among maritime terminals [36]. Also, the adoption of novel technologies, such as IRS can mitigate the degrading effects of fading path-loss [37].

2) Free space optical (FSO) communications

The constantly increasing desire for high-throughput services and the spectrum crunch that is experienced in the RF band has motivated researchers to introduce alternative communication paradigms. A popular solution for high bandwidth transmissions is FSO communication guaranteeing large bandwidth, unlicensed spectrum, high data rate, fast deployment and power reduction, under LoS conditions [38]. However, FSO transmissions are affected by atmospheric effects, i.e., absorption, scattering, and turbulence [39]. As a result, various works have studied hybrid RF/FSO solutions that leverage the

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advantages of both communication technologies, switching to the most appropriate one when environmental characteristics dynamically change, addressing misalignment, resource allocation and energy efficiency issues [40]–[43].

3) Visible-light communications (VLC)

Another technology that has received several contributions in recent years is VLC, using light-emitting diodes (LEDs) to transmit data and avoid impairments of RF communications, such as interference and signal leakage. In maritime environments, VLC can especially facilitate communications of the underwater segment, among UUVs and from UUVs to USVs/ships/UAVs acting as data sinks but also between nodes above the sea surface [44]. In this context, efficient VLC solutions should consider the mobility of maritime IoT deployments and ensure accurate pointing between the VLC transceivers [45] Moreover, the maritime VLC channel model should be thoroughly investigated, since many impairment parameters affect its quality, while its impact to the system's performance is significant [46].

4) Acoustic communications

In underwater communications, long-range transmission can be performed when acoustic waves are employed. In several studies, focusing on the underwater channel characteristics, the main challenges in underwater acoustic communications have been highlighted, including poor quality and highly dynamic nature of acoustic channels, smaller channel capacity compared to RF channels, multipath-rich environment, and larger propagation delay [47]–[50]. Various works have presented efficient multiple access and routing algorithms to improve underwater communication reliability [51]–[53]. Other works have proposed hybrid schemes where acoustic signals are used together with RF and optical signals to combat attenuation effects [54].

C. Performance targets

In order to decide the optimal mix of communication technologies and architectural segments, a wide range of MCN performance targets exists and in many cases introduces trade-offs among conflicting targets and implementation complexity. As it will be presented in the following sections, the various network procedures can be optimized either through conventional optimization techniques and/or ML algorithms [55].

1) Spectral efficiency

An important metric in wireless communication systems is spectral efficiency, given in bps/Hz, representing the achieved data rate over the available bandwidth. Considering that the number of maritime networks' nodes is increasing, while in some areas, MCNs overlap with terrestrial networks, spectral resources become more scarce and a higher frequency re-use is needed, e.g., by deploying aerial BSs or resorting to other frequency bands. Meanwhile, the heterogeneity of MCNs, comprising satellite-aided backhauling calls for intelligent link selection solutions in order to improve the MCNs' spectral efficiency.

2) Energy efficiency/network lifetime maximization

As maritime activities are constantly evolving, an increased number of battery-dependent network nodes, such as UUVs, USVs, UAVs, is deployed. As a result, it is vital to adopt energy-efficient communication techniques with power control [56] and appropriate routing algorithms [57]. The energy efficiency is usually measured in bits/joule, i.e., the number of bits that are transmitted over the energy used for their transmission. In addition, sustainable operation with reduced carbon footprint and operational expenditure for the infrastructure and vessel owners is necessitated. Apart from capitalizing recent advancements in battery technology, WPT is a promising solution to prolong network lifetime of the different MCN segments [58], [59].

3) Communication delay minimization

As URLLC services are highly desirable in the context of critical maritime services, the end-to-end delay is a critical QoS parameter that determines the MCN performance. The reduction of end-to-end delay can be achieved by selecting high throughput wireless data routes through optimal network node selection [60], starting from the physical-layer, considering parameters such as channel quality and the use of multiple antennas for increased diversity, and reaching up to the multiple access layer with non-orthogonal and grant-free schemes.

4) Task and data offloading

Under the mobile edge computing (MEC), edge nodes can provide their computing resources towards bringing data computation closer to the data acquisition points. In this way, latency is dramatically reduced, as long as efficient task allocation algorithms are utilized. In the context of data offloading, several studies aim to improve the cache hit ratio of edge caching-aided networks, defined as the ratio of cached files being requested by the end users over the total number of files that are stored in the cache. Thus, a high cache hit ratio corresponds to higher QoS and backhaul/fronthaul offloading, thus avoiding data fetching from/to remote servers when cache-aided nodes are deployed in the MCN [61].

III. Physical-Layer Design

In this section various research efforts will be analyzed that deal with physical layer issues in the design and deployment of UAV-aided MCNs. In this context, major design goals that should be considered in parallel with the provision of acceptable QoS to end users include proper channel modelling for 5G/6G enabled communications that take into consideration the harsh maritime environment, and data rate maximization along with energy efficient transmissions, in order to deal with the limited battery life of UAVs.

A. Channel modelling for maritime environments

Unlike terrestrial broadband wireless networks, where channel modelling is mainly dictated by a large number of non-line-of-sight (NLoS) components, in a maritime wireless network there can be a large number of direct signal paths. Moreover, sea volatility and extreme weather conditions, especially in the oceans, can have a sever impact on channel conditions. In addition, in maritime communications, where large communication distances are very likely to occur, the Earth curvature is an important factor that influences the basic mechanisms

TABLE III
LIST OF PAPERS ON PHY-LAYER ASPECTS OF UAV-AIDED MARITIME COMMUNICATIONS.

Reference	Maritime topology	Communication target	Method
Timmins et al. [62]	UAV-aided	Channel modelling	FDTD
Liu et al. [63]	UAV-aided	Channel modelling	Multi-bounce components
Gao et al. [64]	UAV-aided	Channel modelling	Ray-tracing algorithm
Rasheed et al. [65]	UAV-aided	Channel modelling	LSTM-DCGAN
Liu et al. [66]	UAV-aided	Link efficiency	Incorporation of weather measurements
Cao et al. [67]	UAV-aided	SE maximization	Normalized LMS for transceiver optimization
Wang et al. [68]	Satellite-UAV-terrestrial	Minimum user rate maximization	Random matrix theory
Ghanbari et al. [69]	UAV-UUV-aided	Outage probability	Theoretical model and simulations
Wanq et al. [70]	UAV-aided	Path connectivity	Theoretical model and simulations
Hong et al. [71]	Space-air-ground-sea integrated network	Data rate maximization	Shape-adaptive antennas
Fang et al. [72]	Maritime cognitive satellite-UAV-terrestrial	CCI mitigation	Random matrix theory
Liu et al. [73]	UAV-aided	Jamming mitigation	DRL
Rahimi et al. [74]	UAV-aided	Energy efficiency maximization	Genetic algorithm
Wang et al. [8]	Satellite-UAV-aided	Minimize energy consumption	Min-Max transformation
Li et al. [75]	Satellite-UAV-terrestrial	Data rate maximization	Successive convex optimization
Li et al. [22]	Satellite-UAV-terrestrial	CCI mitigation	Successive convex optimization
Ai et al. [76]	UAV-USV-terrestrial	Energy consumption minimization	Block coordinate descent
Liu et al. [77]	UAV-aided	Energy consumption and BER minimization	DRL

of the radio propagation [78]. Multipath components can be found in both communication environments, however in the maritime one, their source is due to the water surface, which results to irregular fluctuation that can be introduced in a rough sea [79]. For the same reason, even the specular components of the wireless channel are different, an effect that leads to an important power reduction. In addition to the differences related to the small-scale fading, sea movement may also be responsible for originating highly dynamic shadowing effects. Finally, it is also found that evaporation and elevated ducts is considered as an unexpected ally towards the improvement of the over the sea air-ground propagation. Therefore, the wireless propagation model of the ocean is significantly different from the corresponding terrestrial one.

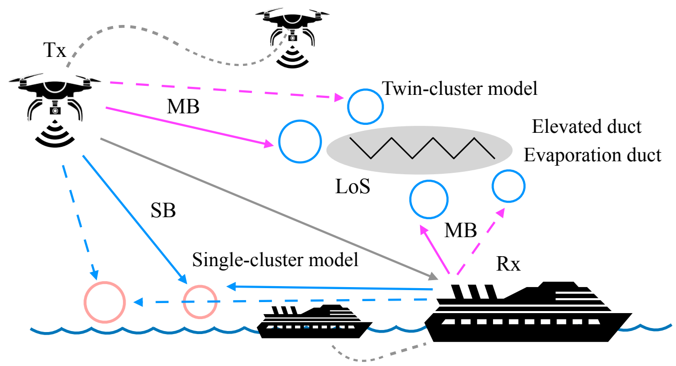

Fig. 3. Elements of the non-stationary multi-mobility UAV-to-ship channel model [63].

In [62], the channel in a UAV-aided MCN was modelled with the help of the finite-difference time domain method (FDTD) method, in an effort to take into consideration the effects of sea surface shadowing conditions on the marine communications channel. Results were restricted for fixed Tx and Rx heights and frequencies below 3GHz. In [63], a novel non-stationary multi-mobility UAV-to-ship channel model is proposed. Fig. 3 provides details of the non-stationary channel where a UAV is transmitting towards a ship. It is assumed that the UAV-to-ship communication operates on the sub-6 GHz spectrum band, but it can also use higher frequencies. In this maritime setting, the fluctuation of sea water and the rough sea surface result in increased reflections, highlighted by solid and dashed arrows in Fig. 3, thus causing multipath fading. Furthermore, evaporation and elevated ducts above the sea surface affect the UAV-to-ship communication link and so, the over-the-sea waveguide effect should be considered. Overall, three major components are observed: the LoS component (gray-colored arrow) denoting direct UAV-to-ship communication; the single-cluster model where the transmitted signals will arrive at the ship by one reflection from the rough sea surface, being described as single-bounce (SB) components (blue-colored arrows); the twin-cluster model denoting that the transmitted signals will experience ducting and/or adverse weather effects, being described as multi-bounce (MB) components (magenta-colored arrows). This model supports multimobility as well, in the sense that vessels, UAVs, clusters, etc. can move to arbitrary locations.

As the authors point out in [64], the majority of related works in channel modelling for maritime communications mainly rely on large scale channel measurement and analysis, that can be extremely time consuming and costly. Therefore, an alternate approach is presented in that work and evaluated, based on the ray-tracing algorithm, in order to model the

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channel from a UAV to a moving vessel. In the same context, the surface morphology is simulated and then the ray-tracing algorithm is applied. Simulation results indicate that the amplitude of the received signal follows the Rice distribution. Although results did not take into consideration sea surface motion, experimental evaluation verified the accuracy of the proposed simulation setup.

In [65] the goal is to incorporate 5G mm-Wave with UAV-aided MCNs. To this end, a channel estimation technique based on ML is proposed, that can be used to a wide variety of applications and surrounding environments, via a fully decentralized generative learning model. Simulation results verify the improved accuracy and downlink data rates of the proposed channel estimation framework. Finally, in [66], the atmospheric ducting effect is described, that can have a severe impact on the quality of wireless communications especially for long ranges. As a result, UAVs, as flying BSs or mobile terminals, may face remote interference, which can be more severe than the corresponding of the traditional terrestrial nodes.

B. Data rate maximization

In the vast majority of related works to data rate maximization, the optimization problem is initially formulated and then solved with computationally efficient techniques. In this context, in [80], the authors investigate a UAV-enabled FSO communication system that could enable a wideband data link with a supporting vessel, when deployed in the Arctic region. To this end, the deployed orientation consists also of a detection unit that can be used for SAR purposes with the help of the UAVs. In the same context, the effects of weather conditions were considered during performance evaluation. According to the presented results, the coexistence of wind and snow had the most severe effect on the FSO link performance followed by fog, snow, and wind, separately. In [67], the authors formulate an mmWave-based UAV-aided MCN optimization problem. In this context, a least mean square (LMS) distributed beamforming algorithm is considered, where transceiver optimization is jointly performed. Simulation results demonstrate the superiority of the proposed normalized approach with respect to the conventional LMS method, both in terms of convergence and spectral efficiency (SE). In the latter case, SE improvement is more evident in the high signal-to-noise ratio (SNR) region.

In [68], the problem of on-demand coverage for maritime hybrid satellite-UAV-terrestrial networks is investigated. To this end, a user-centric clustering approach has been considered, where each vessel is served by a specific group of UAVs and terrestrial BSs (TBSs). Moreover, an edge server has been deployed as well in order to perform central control and signal processing. An optimization framework has been proposed with improved convergence, where the minimum user rate served by TBSs and UAVs is maximized, while guaranteeing the leakage interference to satellite users below an acceptable threshold. In [69], a two hop underwater data transfer transmission scheme has been considered, with the help of UAVs, UUVs, and a buoying relay. In this context, the authors analyze the importance of designing an optimal beamwidth in order to achieve the lowest outage probability of the transceiver link. According to the presented analysis, in scenarios with increased transmission power a wider beamwidth should be employed, in order to mitigate the effects of pointing error. On the contrary, when attenuation is the dominant signal deterioration factor, a narrower beam should be employed.

In [70], the same transmission approach as in [69] has been considered, where analytical path connectivity expressions have been derived, both for the underwater and air link cases. In particular, a UAV-assisted underwater data acquisition scheme is proposed and evaluated in terms of achievable connectivity, where multiple sink nodes deployed on the water surface serve as intermediate relays between under- water sensors (IoT nodes), deployed either as fixed-grid topology or random, and UAVs. The sink nodes receive acoustic signals that are then forwarded to the UAVs via wireless links. An analytical model is derived, validated by simulation results, that calculates path connectivity, taking into account various vital parameters, such as UAV's trajectory, antenna characteristic, stability of sink nodes, etc. Moreover, a UAV-assisted data acquisition edge computing scheme has been proposed as well. Simulation results verify the effectiveness of the proposed approach, where overall performance is evaluated for a number of transmission related factors, such as the underwater environment and the antenna beamwidth.

Finally, in [71], the authors propose an efficient adaptive antenna design, that can alter the produced radiation pattern according to the supported application. This antenna is composed of cylindrical patch antenna sub-arrays and connected to the infrastructure by flexible substrate. In the same context, the authors also highlight the importance of radar-communication integration in the context of MCNs based on the upcoming 6G technology.

C. Interference mitigation

Due to spectrum scarcity, UAVs and MCNs may share the same bandwidth areas. Hence, advanced co-channel interference (CCI) mitigation techniques are required, which is expected to be an unstable factor due to the continuous motion of UAVs. In this context, in [22], various challenges are presented towards the integration of UAVs and MCNs. An important aspect is that vessels follow specific sea lanes and are distributed over large geographical areas. Therefore, on-demand coverage can be provided with the proper placement of UAVs. To this end, the authors analyze various constraining factors, such as the harsh maritime environment which is strongly affected by weather conditions, the difficulty for UAVs to land and charge, as well as the importance of coordination among terrestrial and satellite networks. In the latter case, when UAVs are far away from the coastal area, satellites could be the only choice for wireless backhaul with inevitable large delay and limited communication rate. Finally, as the authors correctly point out, the trajectory of the UAVs can be exploited in order to extract a CCI pattern. In [72] the authors consider a similar topology as the one in [68], where a power allocation strategy is proposed and evaluated based solely on large-scale CSI measurements. To this end, a two-step iterative algorithm has been developed, that converges quickly to the desired solution. The SE can be improved when compared with other power allocation schemes.

Finally, in [73], a DRL approach is presented and evaluated for jamming mitigation in UAV-aided MCN. In this context, two neural networks are properly trained for power allocation and message transmission. According to the presented results, the proposed approach can significantly improve the BER and reduce the overall power consumption.

D. Energy-efficient transmissions

Energy efficiency in terrestrial UAV-aided communication scenarios represents an integral part of these networks design due to the limited battery capabilities of the UAVs. In maritime communications, the power consumption constraints are much more strict, since longer transmission distances are in general required, while in many cases a small number of UAVs is available for communication purposes. In order to improve energy efficiency in MCN, various "traditional" approaches have been proposed including trajectory optimization, handover decisions improvement, while other more maritime communications-oriented have been also examined, e.g., minimizing the USV transmission power.

In this context, in [74] the authors propose a novel approach for the provision of seamless connectivity in a maritime orientation. To this end, a series of connected buoys is deployed over a wide sea-range in order to handle transmission among UAVs and the on-shore data-fusion and control center. The basic goal is to reduce energy consumption by avoiding unnecessary handover triggers. Therefore, the authors propose a handover decision model based on received signal strength. In this context, the formulated problem, that takes into consideration SNR, available data rate, as well as residual energy and handover data, is solved with the help of a probabilistic-based genetic algorithm. Simulation results indicate that the proposed approach can significantly reduce handover triggers when compared to other approaches. In [8], the authors consider a hierarchical satellite-UAV-terrestrial MCN. To this end, the joint link scheduling and rate adaptation problem for this hybrid network is addressed, in an effort to minimize the total energy consumption with QoS guarantees. A key novelty of the proposed approach is that only the slowly-varying large-scale CSI is considered, which can be obtained easily according to the trajectories of UAVs and the shipping lanes of vessels. Performance evaluation is based on reduced complexity approximations, such as the Min-Max transformations. Results indicate that the proposed approach can converge quickly with moderate computational complexity and has a similar performance compared to the optimal solution. Moreover, as it can be shown in Fig. III-D, significant energy consumption improvement over other approaches is obtained, for different cases of occupied time-slots by each vessel. Similar to [8], the authors in [75] also consider large-scale CSI during the joint optimization of trajectory and in-flight transmit power, subject to constraints on UAV kinematics,

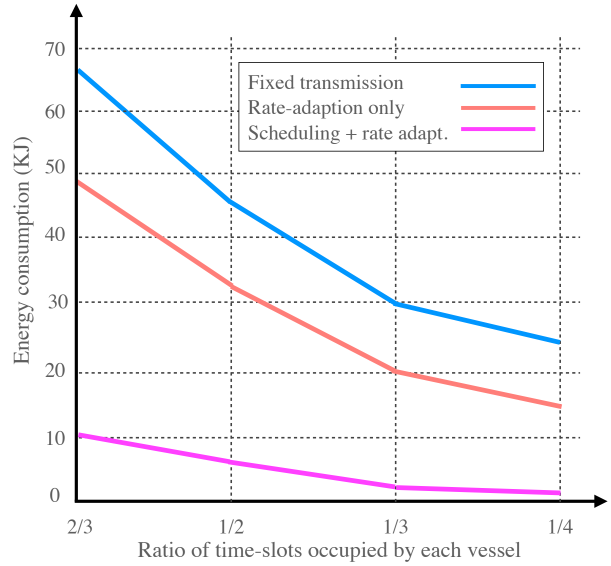

Fig. 4. Energy consumption of the network for different cases of occupied time-slots for each vessel [8].

tolerable interference, backhaul, and the total energy of the UAV for communications.

In [76], a UAV-assisted with IRS-aided technology is assumed in wireless inland ship MEC network architecture for supporting USV communications. The scope of this study is to minimize the total energy consumption by proposing low complexity descent algorithms, which take into account the UAVs trajectory, USVs transmission power, and IRS phase shifts. In [77], in a maritime communication scenario, in which a UAV has been used as relay between two ships, the presence of a smart jammer is assumed. By exploiting information related to the UAV trajectory/power as well as the received jamming power, an energy efficient and BER optimization solution has been proposed that is based on DRL.

Finally, in [71], the authors propose an efficient adaptive antenna design, that can alter the produced radiation pattern according to the supported application. This antenna is composed of cylindrical patch antenna sub-arrays and connected to the infrastructure by flexible substrate. In the same context, the authors also highlight the importance of radar-communication integration in the context of MCNs based on the upcoming 6G technology.

Lessons-learned: In all the aforementioned studies, once the general optimization problem is formulated, it is decomposed to a discrete number of problems equal to the number of output metrics. These problems are solved either via iterative optimization problems that have significantly reduced computational complexity with respect to the initial non-convex problem, or with the help of ML approaches. However, as it will also be discussed in Section VIII, the vast majority of the aforementioned works considers limited network orientations in order to reduce computational complexity. The proper deployment of ML approaches is a challenging research field, both in terms of latency reduction as well as online training and update, due to the harsh and diverse nature of the maritime environment.

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IV. Radio-Resource Management

Proper RRM in UAV-aided maritime communications includes a variety of diverse design goals, such as the maximization of spectral efficiency, proper deployment of UAVs in order to provide efficient network coverage and network lifetime maximization to avoid potential outage especially in long distances from terrestrial networks. Finally, proper authentication mechanisms are of utmost importance as well, since due to the interconnection of a large number of IoT devices, security breaches are more likely to appear. In the following subsections, related works in the aforementioned areas are described, while key considerations are outlined in Table IV.

A. *Cooperative UAV data relaying*

As previously mentioned, UAVs can have a dual role in MCNs: serve either as active BSs in order to provide coverage in distant areas, or act as relay nodes that enhance and re-transmit signals mainly coming from serving nodes located either below or on the surface of the sea. In this context, another typical application of UAV-assisted wireless communications in the maritime sector is for oceanic monitoring networks (OMNs), since they are not restricted by the geographical environment and have advantages on flexible networking configurations. To this end, such an architectural approach, as also mentioned in Section II, consists of two segments, the underwater transmission between underwater sensor nodes (USNs) and sea surface sink nodes (SNs) as well as the RF part, from SNs to ground base stations or UAVs [81]. Therefore, UAVs can act as relay nodes among USNs, SNs, and TBSs.

In [82], the performance of a buoy communication mode selection strategy has been evaluated, where UAVs can act as relay nodes. All UAV-related optimization issues (i.e., trajectory, power consumption, time slot allocation, etc), are separately treated in order to relax computational burden. According to the presented results, the proposed algorithm can significantly improve the minimum throughput of the ocean surface drifting buoys. In [83], an iterative optimization algorithm has been proposed that reduces average transmission delay and increases transmission success ratio, taking into consideration the motion of container vessels. In [84] a narrow-band IoT infrastructure is used for tracking containers transported by marine cargo vessels, while operating near the coastline. To this end, UAVs are used as intermediate relay nodes. Extensive system-level simulations were performed indicating that the relay-assisted approach can significantly improve link quality with respect to the standard vessel-BS connection. In [85], the authors investigate a multi-UAV assisted cooperative transmission to maximize the total throughput under the constraints of outage probability, transmit power and available channels. To this end, a heuristic algorithm is employed to solve the optimization problem. A significant novelty of the presented work is that performance evaluation considers in general a large number of USVs and UAVs compared to other state of the art approaches (i.e., 15 UAVs, 50 USVs). According to the presented results, the performance of the proposed approach is quite close to the optimal solution. In [95], a UAV-USV cooperative communication scenario in smart ocean networks has been investigated with the scope to improve the quality and reduce the cost. To this aim, a matching algorithm has been proposed to transform the task assignment into a one-to-one matching problem between UAVs and USV coalitions.

Finally, in [87], a more generic cooperative approach among

TABLE IV
List of papers on resource management for UAV-aided maritime communications.

Reference	Maritime topology	Resource management target	Method
Ma et al. [81]	UAV-aided	Network lifetime maximization via relay transmission	Optimization based on network lifetime maximization
Chen et al. [82]	UAV-aided	Delay and message loss minimization via relay transmission	System-level simulations
Che et al. [83]	UAV-aided	Reduction of transmission delay via UAV-assisted relay transmission	Iterative optimization
Kavuri et al. [84]	UAV-aided	Delay and loss probability	Simulation framework
Lyu et al. [85]	UAV-aided	Relay transmission	Joint optimization of power and trajectory
Liu et al. [86]	UAV-USV-aided	Task allocation	Matching-coalition game
Jia et al. [87]	UAV-USV-aided	Heterogeneous networks collaboration	Matching algorithm
Cao et al. [88]	UAV-aided	Delay minimization, network throughput maximization	DRL
Jia et al. [89]	Satellite-UAV-Terrestrial	Multiple-tier networks cooperation	Matching algorithm
Tang et al. [90]	UAV-aided	NOMA-aided throughput maximization	Problem decomposition
Ma et al. [91]	UAV-USN-aided	NOMA-aided network lifetime maximization	Weight-based matching
Tang et al. [90]	UAV-aided	Cooperative data collection	Problem decomposition
Xie [92]	UAV-aided	Routing optimization in FANETs	Enhanced link-state routing protocol
Chaundry et al. [93]	Satellite-UAV-Terrestrial	Security enhancement	Real or random oracle model
Khan et al. [94]	Satellite-UAV-Terrestrial	Security enhancement	Elliptic curve cryptography

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LEO satellites and HAPs is presented, that can leverage space-air-ground wireless communications. Since the complexity of the corresponding optimization problem is significantly increased when compared to other standard 1-tier networks, a satellite-oriented restricted three-sided matching algorithm is proposed to deal with the matching among users, HAPs, and satellites. In the same context, in [88], an integrated communication network for terrestrial, sea and high-altitude platform is proposed and evaluated. To this end, the problem of node accessing is formulated under various constraints and solved with the help of DRL. Simulation results demonstrate that the proposed node access mechanism can effectively improve data transfer rate, average device-to-device (D2D) delay and network throughput.

B. Non-orthogonal multiple access

In NOMA transmission the same resource block is shared among a group of nodes in order to improve SE and leverage multinode connectivity. In this context, on one hand the NOMA group should be carefully chosen in order to minimize inter-user interference and on the other hand advanced signal reception techniques are required for successive interference cancellation [96]. Following a similar approach for hybrid satellite-UAV-terrestrial deployment as the one in [8] and [75], where TBSs and UAVs form virtual clusters in a user-centric manner, NOMA transmission has been adopted per cluster in [89]. The spectrum sharing has been considered between nearshore clusters and marine satellites. In this context, a joint power allocation scheme has been proposed, based solely on large-CSI. According to the presented results, the ergodic sum rate has been maximized at a low cost. Fig. 5 shows the ergodic sum-rate performance where the superiority of NOMA due to its flexibility in separating users in the power domain over orthogonal multiple access (OMA) alternatives from [97], [98] is observed. In [90], NOMA groups are formulated by various vessels that are served either by UAVs or TBSs. In order to reduce overall system cost, a single UAV has been considered with a trajectory dictated by the vessels located in the blind zones. In the same context (i.e., cost reduction) both the UAV and vessels are equipped with a single antenna. To solve the non-convex formulated problem, the authors first decompose it into a transmit power allocation subproblem and a transmission duration assignment subproblem. According to the presented results, SE can be improved compared to other approaches.

C. Network lifetime maximization

The integration of various technologies in modern MCNs, such as sensing equipment and advanced power supply infrastructure, necessitates a holistic performance evaluation that takes into account the role of various actors in the MCN ecosystem [99]. Network lifetime maximization is a significant technical challenge that on one hand can reduce outage probability and on the other hand ensure the provision of end to end high data rate applications. To this end, the works in [91] and [81] propose an architectural approach where UAVs are used as relay nodes between SNs and TBSs.

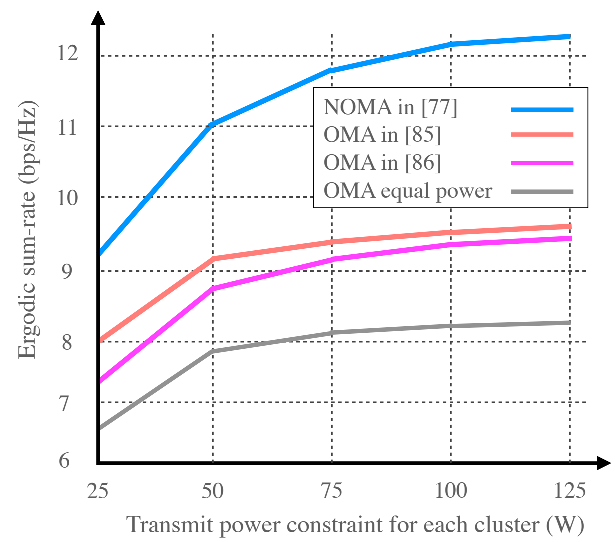

Fig. 5. Ergodic sum-rate results for various NOMA/OMA power allocation schemes [89].

In this context, and in an effort to improve network's lifetime, resource allocation and UAV deployment issues are modelled as a non-convex optimization problem. This problem is then decoupled to two separate sub-problems: delay minimization for the UAV-SN part and and lifetime maximization for USN-SN communication. Simulation results verified the improved performance of the proposed approach compared to other time division multiple access (TDMA) schemes.

In [92], a routing protocol based on optimized link-state routing protocol is proposed and evaluated, based on the node link expiration time and residual energy. This approach can significantly improve end-to-end delay, packet transmission rate and routing overhead.

D. Security considerations

The integration of various and diverse communication networks in order to form a MCN, has raised security and privacy concerns, especially in the forthcoming 6G-IoT era. In [93], the authors propose a lightweight authentication protocol for a 6G-IoT MCN. The proposed approach has been evaluated with the help of formal security assessment methods and compared to other security mechanisms. The presented results indicate that the proposed approach achieves a better security-to-efficiency trade-off compared to other state-of-the-art approaches. In [94], the authors propose a resource friendly authentication scheme for MCNs based on elliptic curve cryptography. According to experimental evaluation, the proposed approach has improved performance compared to other approaches in terms of computational and communication cost.

Lessons-learned: It becomes apparent from the analysis of the previous subsections that the joint consideration of different RRM goals can be a computationally intensive task, due to the multiple and diverse design goals, as well as related constraints. As in the previous section of physical layer design aspects, a similar approach has been considered in RRM problems as well, via problem decomposition and

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TABLE V
LIST OF PAPERS ON CLOUD/EDGE SOLUTIONS FOR UAV-AIDED MARITIME COMMUNICATIONS.

Reference	Maritime topology	Cloud/edge target	Method
Dai et al. [100]	UAV-USV based	Offloading delay	Penalty convex-concave procedure
Hassan et al. [101]	UAV-based	Maximize network profit	Bender decomposition
Yang et al. [102]	UAV-based	Time delay and energy consumption	Upper confidence bound
Zeng et al. [103]	UAV-based	Latency and energy consumption	Multi-agent DRL
Xu et al. [104]	Satellite-UAV-Terrestrial	Resources utilization and latency	DRL
Liu et al. [105]	UAV-based	Minimization of the latency	DRL
Zeng et al. [106]	UAV-USV based	Reduction of the execution time	Incentive-based collaborative
Hassan et al. [107]	Satellite-UAV-Terrestrial	Weighted computational/ communication sum-rate	Bender and primal decomposition
Dai et al. [108]	UAV-based	Minimization of the mission time	DRL

iterative optimization approaches. In this context, hierarchical ML training can be applicable, where the outputs of ML training in the physical layer are properly integrated in ML approaches for RRM design and optimization.

V. CLOUD/EDGE COMPUTING AND DATA OFFLOADING

The recent mobile communication architecture advances have included MEC as an efficient approach for providing powerful computing capability and low latency to the users. This approach has been also adopted in MCN, where the edge servers, which in several cases are mounted at the UAVs, are deployed close to the ship terminals (or maritime IoT) and have been used to offload computing tasks. Next, related works on mobile edge computing and data offloading in maritime UAV-assisted communication scenarios are discussed, while key considerations are outlined in Table V.

A. *Mobile edge computing*

An important research objective in UAV-assisted MEC studies that is also adopted in MCN is to simultaneously efficient utilize communication, energy resources, by taking also into account latency and computational complexity constraints. These optimization formulations have been also adopted in the following papers, which have been solved with the aid of conventional and DRL approaches. In [101], UAV-assisted maritime IoT communication network has been studied, with the scope to maximize the network profit in MEC-UAVs deployments. The combinatorial optimization problem that has been formulated has been solved using an iterative algorithm

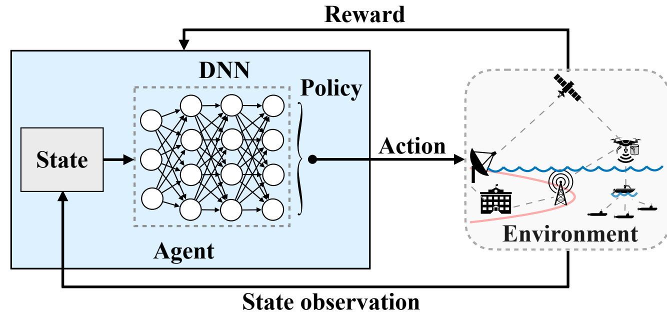

Fig. 6. DRL architecture in the context of a UAV-aided MCN.

that is based on Bender decomposition approach. The simulation results presented, demonstrate the near optimal solutions offered by the proposed approach, in an efficient convergence time. In [103], UAV-assisted maritime communication system is investigated, in which UAVs have been employed as mobile data centers in a mobile edge communications, computing, and caching framework. In order to improve the caching rate a multi-agent DRL technology has been used, which predicts users' preferences and reduces task latency. It is shown that a considerable reduction on the task latency and energy consumption is obtained. In [109] and [102], a space-air-ground-edge integrated maritime communications network has been assumed, in which the UAVs can be used as edge servers in order to offload tasks of users. The scope of this paper is to propose an algorithm for selecting the best UAV edge server, which results to a multi-armed bandit problem, taking also into account budget constraints as well as other weighted factors such as delay and energy consumption. Based on the upper confidence bound algorithm, the UAV selection problem can be solved and the resulting simulation results prove the effectiveness of the proposed approach in terms of lower offloading latency and weighted latency-energy cost. In [104], in a similar system model as it is the one investigated in [102], a joint communication and computation resource allocation problem has been introduced in order to minimize the resource utilization and computational delays. Using a DRL approach for resolving the optimization problem, it resulted to an important improvement of the utilization efficiency of resources as well as a reduction to the reduction of the task implementation latency. Fig. 6 illustrates a centralized DRL architecture where a UAV-aided MCN is optimized following a reward-based procedure, taking appropriate actions to maximize its utility function.

In [105], a two-layer UAV-enabled MEC maritime communication network has been investigated, in which parallel computation of tasks offloading with different amount of data in different virtual machines has been studied. In this framework, a latency minimization problem has been formulated, which takes into account both communication and computation aspects. This problem has been solved using deep Q-network and deep deterministic policy gradient algorithms that aim to find optimal flight trajectories and number of virtual machines participation. The various results presented proved the reduction to the total average latency as compared

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to conventional approaches. In [107], a space-air-sea non-terrestrial network has been studied, in which LEO-MEC satellite allows users to offload data and UAV-MEC is employed for backhauling purposes. In an effort to maximize the weighted computational and communication sum rate, a joint Bender and primal decomposition algorithm has been proposed. Based on this approach an near optimal performance is achieved with an efficient convergence time. In [110], a space-air-ground-aqua integrated network architecture is studied, which is combined with MEC technology. In that paper several research challenges were discussed, while various future direction were also proposed.

B. Data Offloading

In the following data offloading works, the main objective is also a time-related reduction. In [100], a UAV-assisted data offloading model is proposed for maritime communications, which takes into account the mobility of container vessel, the UAV movements, and the wireless propagation over the sea. The problem is solved using the penalty convex-concave procedure, and at the various simulation results presented, it was shown that the proposed algorithm can efficiently reduce the average offloading delay and offloading success ratio. In [106], a UAV-USV-based collaborative network with maritime cloud servers is introduced. In this collaborative computation offloading framework, the UAVs offloading ratio, to the USVs fleets, is investigated using an incentive-based collaborative computation offloading scheme. The simulation results indicated a significantly reduction of the computation tasks overall execution time. In [108], a UAV-assisted data collection and data offloading system in marine IoT has been investigated. The objective is to minimize the total mission completion time, by taking into account UAV trajectory, data offloading capabilities, buoy-UAV association, and the transmit power. The mixed integer non-convex problem that is introduced is solved based on a delayed deep deterministic algorithm. The simulation results presented, prove the effectiveness of the proposed scheme for reducing the total mission completion time.

Lessons-learned: In all the MEC-related aforementioned studies, the most challenging objective is to optimize the UAV-assisted MEC network and simultaneously satisfy the various constraints induced by the MCNs, such as the computational complexity, latency, and energy efficiency. Towards this aim, DRL approach seems to be the most widely adopted methodology used in various maritime network architecture scenarios. As far as data offloading is concerned, the main objective in most cases is to reduce the delay based on various approaches.

VI. UAV TRAJECTORY OPTIMIZATION

Trajectory optimization is another important aspect of UAV-aided MCNs, since it is directly related to a considerable number of performance metrics described in the previous sections, such as network lifetime maximization and energy consumption minimization. Moreover, in emergency situations, proper trajectory design can reduce overall network installation time and leverage high quality connectivity. It is noted that UAV-aided maritime communications engender peculiar communication challenges on top of the ones induced by the wireless medium. More specifically, these type of communications are, in general, characterized by dynamic conditions (in terms of both velocity and direction of motion) for both end-sides of the UAV-to-vessel link. Moreover, in scenarios where UAVs are employed as relay nodes, an enormous difference between the distances of the source-to-relay and relay-to-destination communication links exists. Moreover, maritime communication environment is characterized by low density population, low interference probability, stochastic impact of marine winds, and time varying uplink and downlink traffic. Therefore, these new additional parameters/constraints, result to a totally different and more complex optimization problem that should be formulated for proposing the best trajectory and scheduling algorithms. In the following subsections, related works are categorized according to communication performance enhancement and search and rescue procedures.

A. Enhancing communication performance

In this subsection various recent works will be analyzed that mainly employ efficient trajectory optimization algorithms towards improving link connectivity under various constraints, such as transmission power and provision of minimum data rate. In [111] an open simulation strategy has been developed with the help of Matlab/Simulink for UAV and USV cooperation and interaction with the environment. Therefore, UAV trajectory can be visualised with the help of a flexible software tool that can be executed in various platforms. In [112], a multi-UAV maritime IoT topology has been considered, used to collect information from SNs. In this context, the goal is to find the optimum placement of UAVs and SNs that minimizes overall energy consumption. The integer linear programming optimization problem is formulated and then solved with the help of the Gurobi solver. In [113], the optimum placement of UAVs is investigated for off-shore relay communications. To this end, a minimum-maximization optimization problem of link capacity is formulated and solved with the help of particle swarm optimization (PSO) algorithm.

In [114] - [115], a non-convex optimization problem is formulated in order to reduce the energy consumption in a UAV when used as a relay node that gathers and processes information from multiple deployed buoys. In this context, the communication time scheduling among the buoys and the UAV's flight trajectory subject to wind effect are jointly optimized. The formulated optimization problem is solved with the help of the successive convex approximation (SCA) method, based on a proposed cyclical trajectory design framework that can handle arbitrary data volume efficiently subject to wind effect.

In [116] a MCN is considered with UAVs, buoys, and underwater sensors. The goal is to maximize energy efficiency by jointly optimizing the transmit power of buoys and sensors, scheduling their transmissions, as well as designing the UAV's trajectory. To this end, three separate sub-problems are considered in an effort to relax computational burden, that are solved

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with the help of SCA method. According to the presented results, the adopted method has improved convergence time when compared with other methods. In [117], the authors evaluate the performance of fast UAV trajectory planning algorithm based on the Fermat-point theory for a maritime IoT with USVs. Results indicate that the proposed approach can significantly improve data collection rate of USVs and provide fast convergence at the same time. In [118], a multi-relay orientation has been considered, where the goal is trajectory optimization with the help of dual Q-learning. In this context, the objective is to minimize the total average loss and thus improve link quality. In [119], considering only large-scale CSI, an algorithm is proposed based on problem decomposition and successive convex optimization for effective power allocation and trajectory planning in a hybrid satellite- UAV-terrestrial MCN. In [120], a UAV relay orientation has been considered, where the goal is to maximize overall data rate. For the special case of a single user, the authors derive a semi closed-form expression of UAV placement. In the same context, an algorithm to find the optimal UAV placement for the general case with multiple users has been presented and evaluated. In [121], a UAV is used for data collection from various sensor nodes. The goal is to optimize UAV trajectory in order to minimize total energy consumption, maximize data rate along with the flight duration of the UAV. The optimization problem is formulated and solved with the help of PSO, for various CSI scenarios (i.e., full or limited sensor node position information). To this end, a Kalman filter is used to improve the position estimation errors. Finally, a similar approach with PSO modelling has been also followed in [122] to solve the random task allocation problem of multiple UAVs and the two-dimensional route planning of a single UAV.

B. Improving maritime search and rescue

UAVs can be alternately deployed for search and rescue purposes in MCNs, where the primary goal is to reduce overall network delay. In [123], various research challenges are presented and investigated in the field of wide are monitoring in MCNs with the help of UAVs, such as optimum number and deployment of UAVs as well as scheduling algorithms for patrolling and recharging UAVs. In [86] the authors consider a maritime emergency communication scenario, where a UAV acts as a BS and can communicate with a number of active nodes in the sea. The goal is to jointly optimize power allocation and trajectory of the UAV, in order to maximize system's throughput. In such an emergency scenario, the received signal from an arbitrary node is broadcasted to the individual users within the close proximity of the node. The optimization problem is formulated and solved with the help of a loop iterative algorithm. In [124], an extended search algorithm is presented and evaluated with the help of MATLAB for efficient and rapid maritime search. The presented results reveal a close relationship among the height of the UAV and the overall rescue time. In [125], a computational tool has been presented and evaluated towards leveraging communications range and capacity limits of ad-hoc networks of UAVs operating in maritime scenarios. To this end, performance evaluation consisted of two scenarios: collaborative search and tracking of targets and circular formation flight for detection of external threats to ship convoys. In [126], a cooperative communication model among UAVs and USVs in MCNs is analyzed, for SAR purposes. In this context, RL is used to plan the optimum search path and improve overall throughput. The authors evaluated achievable throughput for various reward functions in order to improve the data throughput of the system.

Moving a step forward, in [127], the problem of underwater object detection is investigated, via the collaboration of UAVs, USVs, and UUVs, in a scenario where acoustic communications have been considered for the underwater communication link. In this context, the overall strategy is divided into the search phase and the track phase. In each one of the two phases, the goal is to maximize the search space and minimize the terminal error respectively. An improved PSO algorithm has been deployed, that can be executed either in a centralized or in a distributed mode. According to the presented results, the joint UAV-USV-UUV integrated system can be more efficient from the USV-UUV for the search and track procedures. In [128], the authors optimize the trajectory of a UAV when deployed for maritime radar wide area persistent surveillance with the objective goals to minimize power consumption maximize mean probability of detection, and minimize mean revisit time. To this end, a multiobjective PSO algorithm has been employed and evaluated for two realistic operational scenarios.

Lessons-learned: UAV trajectory optimization is a very demanding and complex aspect of the UAV-assisted MCN due to various reasons, such as the dynamic nature of the network elements, the stochastic impact of the winds and the waves. The most widely adopted criteria for this type of optimization are the throughput maximization and the energy efficiency. On the other hand, in SAR scenarios, multi-objectives problems are obtained, which are usually related to the number of UAVs, the power consumption, the UAVs trajectory, the overall rescue time etc.

VII. Experimental Studies

In this section representative recent works are analyzed that deal with experimental evaluation of UAV-aided MCNs, considering various design aspects as described in the previous sections. In this context, in [129] preliminary results are presented towards the development of an autonomous ocean observing system using miniature underwater gliders that can operate with the support of UAVs and USVs for deployment, recovery, battery charging, and communication relay. According to the presented results, the individual components are shown to be pressure tolerant retaining functionality at pressure equivalent to 200m depth. In [130], experimental demonstrations have been performed in order to evaluate the feasibility of using UAVs as a sea-surface base for underwater communication with an UUV. According to the presented results, UAVs can provide an efficient communication link for distances near the shore, achieving at the same time robust hovering control.

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TABLE VI
LIST OF PAPERS ON UAV TRAJECTORY DESIGN FOR UAV-AIDED MARITIME COMMUNICATIONS.

Reference	Maritime topology	Trajectory optimization target	Method
Velasco et al. [111]	UAV-based	Reduction of development and delivery times	Simulink-based open simulation strategy
Zhang et al. [112]	Multi-UAV-based	Energy consumption	Gurobi solver
Guan et al. [113]	UAV-based	Link capacity	PSO
Zhang et al. [114], [115]	UAV-based	Energy consumption	SCA
Zhixin et al. [116]	UAV-based	Joint resource allocation and trajectory design	SCA
Lyu et al. [117]	UAV-USVbased	Data collection rate of USVs	Fermat-point theory
Li et al. [118]	UAV-based	Losses minimization	Dual Q-learning
Li et al. [119]	Hybrid Satellite-UAV-Terrestrial	Maximization of minimum data rate	Successive convex optimization
Zhang et al. [120]	UAV-assisted	Data rate maximization	One-dimensional linear search
Ho et al. [121]	UAV-assisted	Energy minimization, throughput maximization	Kalman Filter, PSO
Yan et al. [122]	UAV-assisted	Task allocation	PSO
Liu et al. [86]	UAV-based	Throughput maximization	Loop iterative algorithm
Zuo et al. [124]	UAV-based	Search time improvement	Square search
Oliveira et al. [125]	UAV-based	Collaborative search and tracking	Simulation tool
Yang et al. [126]	UAV-USV-based	Collaborative search and rescue	RL
Wu et al. [127]	UAV-USV-UUV based	Collaborative search and rescue	PSO
Brown et al. [128]	UAV-based	Trajectory optimization	PSO

In [131], a channel measurement campaign was performed for the communication between a UAV and an USV at the S-band. The analysis included large-scale and small-scale channel characteristics, including path-loss, shadow fading, and multipath fading. In [132], an experimental study is presented concerning the deployment of a USV and a UAV in an autonomous collaborative communication system. To this end, two communication scenarios are evaluated, the first one including a direct link among the TBS and the USV, while the second one considers the UAV as a relay node with respect to the aforementioned link. To this end, directional antennas are placed on the UAV and the USV with the appropriate steering mechanisms to align radiation patterns. In [133], the authors evaluate the RF propagation at MCNs using the BLUECOM+ solution, which consists of a multi-hop aerial backhaul network. To this end, a height control approach has been presented and evaluated, taking into account all reflected signals in order to maximize reception quality. The relay node positioning problem was defined as an optimization problem and solved using the PSO technique. According to the presented results the PSO approach outperformed the trivial methods in terms of overall throughput, such as fixed or random height selection.

In [134] a UAV-aided MCN network is evaluated when used for rescue purposes, where applicability of Long Term Evolution (LTE) is investigated. At the first step, a detailed maritime channel model is developed and implemented. The model is then evaluated via hardware implementation. In [135], potential benefits from the integration of UAVs in SAR operations with LTE networks are evaluated. To this end, the authors develop a resource-guaranteed scheme based on persistent scheduling, using an open-source LTE stack. The approach is evaluated with a laboratory setup using software-defined radio modules. According to the presented results, latency and reliability can be significantly improved. In [136], a novel multi-link approach based on LTE networks is proposed in an effort to increase overall network throughput by aggregation. Moreover, large scale experiments have been conducted and published. According to the presented results, the adopted multi-link approach can enable smooth handovers between different networks. In [137], field trials were performed concerning the cooperation between a UAV and a USV. Finally, in a similar context in [138], an experimental evaluation took place considering various UAVs, USVs, and UUVs. To this end, various operational scenarios were considered. In all scenarios, including direct and relayed connection, the network was found to be reliable.

Lessons-learned: It becomes apparent from the aforementioned studies that large-scale channel measurement campaigns are an essential step towards accurate performance evaluation of various UAV-assisted MCNs, especially in the upcoming 6G era. In the same context, experimental evaluation in multi-UAV or USV scenarios can provide useful insights towards their usage in large distances from shore for vessel support.

VIII. OPEN ISSUES

The integration of UAVs in MCNs can provide tremendous gains in coverage, delay reduction, reliability and deployment flexibility. As research on this areas has only recently started, there are several open issues and interesting research directions to explore.

A. Physical-layer issues

The deployment of a large number of transmitting antennas results in massive MIMO (mMIMO) configurations. In general, such configurations can provide improved spatial separation among active nodes via the generation of highly directional lobes. Therefore, both SE and EE can be leveraged [139]. However, in a MCN orientation, the deployment of

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mMIMO antennas in UAVs would result in increased installations costs and overall hardware complexity. In this context, decentralized architectures (d-MIMO) are an active area of research interest, as significant advantages compared to the centralized structures can be provided [140]. In particular, d-MIMO systems can reduce spatial correlation, increase the diversity and multiplexing gain, and reduce the average path-losses through effectively shortening transmission distances, which can be beneficial in MCNs. Another promising technique is related to IRS-aided UAV networks. In such cases, wireless channel quality can be significantly enhanced through the deployment of UAVs carrying IRSs that appropriately perform phase shifting of the relayed signals [141], [142]. Another interesting research topic is the design and implementation of a measurement campaign for 6G carrier frequencies. So far, even up to date works, such as the one presented in [63] have considered frequencies up to 5GHz during performance evaluation. Finally, the integration of visible light and acoustic communication schemes in UAV-assisted MCN should be investigated, since these types of technologies will provide efficient and reliable solutions to the overall architecture.

B. UAV-aided non-orthogonal multiple access

UAV-aided MCNs possess high flexibility due to the existence of LoS conditions and the re-positioning capabilities of UAVs. As NOMA schemes have been increasingly popular in recent years, due to their potential to improve the performance of mobile networks, the development of NOMA solutions for UAV-aided MCNs is an important research area. Such algorithms should optimize the UAV trajectory and positioning in order to maintain channel asymmetry between co-existing network nodes, thus maximizing the spectral efficiency of the transmission [143]. Moreover, the integration of NOMA in mobile edge networks, where task allocation, caching location and power allocation for NOMA are jointly determined represents another highly efficient solution [144], [145]. Meanwhile, the gains of NOMA in buffer-aided networks have already been highlighted in several studies, further strengthening communication reliability at the cost of a slight delay increase [146]–[148].

C. Machine learning

In the majority of related works to key performance indicator optimization in UAV-aided MCNs and performance evaluation, simple network topologies have been considered (i.e., reduced number of UAVs, service nodes, etc.) in order to reduce the computational complexity of the proposed optimization approaches. In the same context, the considered works examine specific sub-problems of MCNs, such as UAVs for data relaying, communication among UAVs and USVs, as well as communication among UAVs and specific data collection points on sea surface. However, a more accurate performance evaluation requires large-scale orientations to be considered, employing a realistic number of active IoT devices, UAVs and vessels, for a holistic network design. To this end, due to the multiparameter nature of such orientations (increased number of access points and communication links,

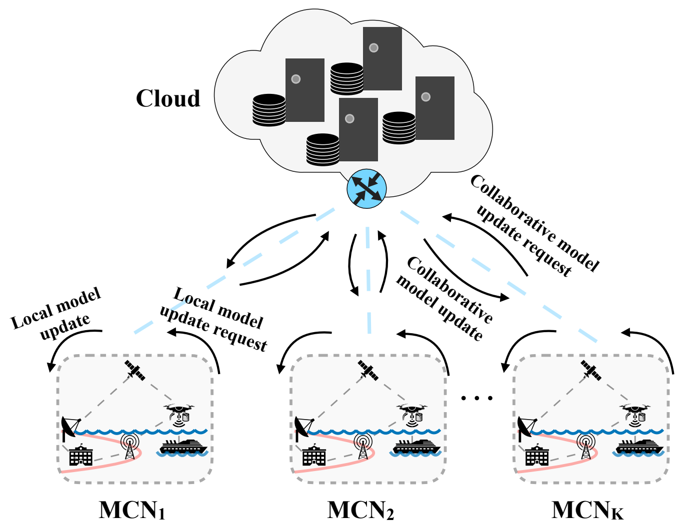

Fig. 7. Federated learning architecture of a maritime network, comprising K UAV-aided coverage areas.

harsh maritime environment) advanced ML algorithms, such as DRL can be quite effective, due to their inherent ability to adapt to various network conditions and perform corresponding adjustments [149], [150]. However, as UAV-aided MCN operation is threatened by increased communication and energy costs, transfer and federated learning (FL) represent promising solutions to overcome these issues [151], especially in edge caching scenarios. First, transfer learning initially extracts features, such as file popularity on a base network, relying on a generalized dataset. Next, these features are used to facilitate DRL agents on edge UAVs to converge to the optimal caching policy, thus reducing the UAV energy consumption. Another radical learning paradigm, involves federated learning, leveraging the observations of multiple DRL agents at different edge nodes for training a shared model. The main benefit of FL in UAV-aided MCNs is the reduction in communication costs, as FL uses locally stored data and only computes updates to the global shared model of the coordinating node. Fig. 7 depicts a federated learning architecture where a maritime network spanning K UAV-aided coverage areas, exploits local model updates to improve the efficiency of the global collaborative model.

D. Security and safety

It is critical to develop secure UAV-aided communication systems to overcome different attack types on communication reliability [152] and the safety of critical infrastructures. In this context, for MCNs relying on UAVs, disrupting the UAV's transmissions by identity forging might be difficult to identify especially in networks of UAV swarms. Thus, UAV authentication and analysis of the received information content is needed, with possible implications for the delay performance [93]. Moreover, in intelligent maritime transportation systems, UAV swarms coordinate to perform various procedures. Still, there exist several vulnerabilities that attackers can exploit towards injecting false data and disputing UAV manoeuvring and collision avoidance systems. In cases where data privacy issues arise, resorting to federated learning is preferable as the federated averaging algorithm builds a global model by aggregating the weighted average of locally updated model at each network device [153]. Finally, even though UAV-aided MCNs ripe the benefits of high mobility, low cost, on-demand resource provisioning, and LoS connectivity, they might be vulnerable against eavesdroppers [154], [155]. As a result, distributed and low-complexity physical layer security (PLS) algorithms must be developed that will be suited to UAV-aided MCNs, exploiting advancements in the field of ML for autonomous operation [156]

E. Advanced edge maritime services

An intrinsic characteristic of current MCNs is the intermittent connectivity due to limited coverage. As maritime services will target at autonomous operation of ships, equipment and unmanned vessels, real-time data processing is of utmost importance. UAV-aided MEC can alleviate this issue, as data will be processed locally, thus avoiding the excessive use of backhaul link [157]. The deep integration of UAVs, USVs, and UUVs can lead to optimal computing task allocation and real-time data collection, thus minimizing network latency. Efficient edge computing and caching algorithms should consider processing capabilities jointly with the trajectories of the unmanned vehicles, and their energy constraints in order to maintain high UAV availability in the network [158], [159].

F. UAV swarm intelligence

The autonomous operation of UAV-aided MCNs is critical either for providing wireless coverage to ships and unmanned vessels or for edge computing and caching purposes. The ad-hoc formation of UAV swarms requires reliable inter-UAV connectivity and distributed intelligence with UAVs exchanging data regarding their velocity and trajectory in order to avoid collisions and maximize the coverage and task offloading capabilities [160]. Still, wireless communication issues might arise related to delay in data exchange, channel quality degradation, energy constraints, and harsh meteorological conditions affecting UAV stability. In this context, ML-based algorithms, e.g., through bandit-based channel prediction can alleviate issues related outdated channel state acquisition [56], while WPT solutions and joint trajectory optimization for swarms of UAV could be considered as promising approaches for optimizing the energy management of these systems. These types of problems become much more complicated to be solved in use cases, where a satellite segment is required to be present, in a research field that a lot of work has to be done.

IX. Conclusions

The introduction of UAVs in wireless networks has allowed increased deployment flexibility and dynamic resource provisioning, aligning with 6G ubiquitous connectivity goals. In maritime communications, integrating UAVs to complement shore- and satellite-based deployments provides an intermediate aerial layer that overcomes the limited coverage of terrestrial base stations and increased latency and narrow-band links of satellites. This survey has presented the role of UAVs in maritime network architectures, where they enable a plethora of maritime IoT and broadband service use cases. In addition, various algorithms relying on conventional optimization and machine-learning techniques have been discussed, addressing physical-layer, resource management and cloud/edge computing and caching issues. Furthermore, the important area of UAV trajectory design for maritime communications and search and rescue has been reviewed while current efforts in experimental implementation have been presented. Finally, several important open issues towards efficiently integrating and exploiting UAVs for maritime activities in the 6G era have been outlined, aiming to attract high research interest in this important domain. A major takeaway from this survey is that a strong theoretical framework has been set for UAV-aided MCNs, optimizing important performance metrics in a wide-range of deployment scenarios. However, there exists a gap among theoretical gains and practical large-scale implementation, as the field of UAV-aided MCNs has only started to gain traction.

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