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Article

A Survey on Integrated Sensing, Communication, and Computing Networks for Smart Oceans

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Abstract: The smart ocean has been regarded as an integrated sensing, communication, and computing ecosystem developed for connecting marine objects in surface and underwater environments. The development of the smart ocean is expected to support a variety of marine applications and services such as resource exploration, marine disaster rescuing, and environment monitoring. However, the complex and dynamic marine environments and the limited network resources raise new challenges in marine communication and computing, especially for these computing-intensive and delay-sensitive tasks. Recently, the space–air–ground–sea integrated networks have been envisioned as a promising network framework to enhance the communication and computing performance. In this paper, we conduct a comprehensive survey on the integrated sensing, communication, and computing networks (ISCCNs) for smart oceans based on the collaboration of space–air–ground–sea networks from four domains (i.e., space layer, aerial layer, sea surface layer, and underwater layer), and five aspects (i.e., sensing-related, communication-related, computation-related, security-related, and application-related). Specifically, we provide the key technologies for the ISCCNs in smart oceans, and introduce the state-of-the-art marine sensing, communication, and computing paradigms. The emerging challenges with the potential solutions of the ISCCNs for smart oceans are illustrated to enable the intelligent services. Moreover, the new applications for the ISCCNs in smart oceans are discussed, and potential research directions in smart oceans are provided for future works.

Keywords: smart oceans; space–air–ground–sea integrated networks; integrated sensing, communications, and computing

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1. Introduction

1.1. Background of Smart Oceans

As an extension of terrestrial networks, the increasing number of marine objects has been deployed for different marine activities, thus yielding the paradigm of smart oceans [1], which have developed rapidly and enabled numerous applications and services, such as marine transportation, undersea explorations, monitoring and management, disaster prevention, etc. In smart oceans, a large number of marine objects monitor the ocean environment and generate a large amount of oceanic data for analyzing and processing [2], resulting in the requirements for data transmission and computational analysis. The traditional terrestrial communications cannot meet the needs of large-scale and low-delay transmission due to the complex and dynamic characteristics of ocean environments [3]. Smart oceans, which connect the marine objects with sensing, communication, and computing capacities, have been envisioned as the promising paradigm to enhance the convenience of marine activities for human beings, and it has attracted much attention of the governments, industries, and academia. Although the unique characteristics of a smart ocean can provide lots of benefits, there remains a lack of efficient communication and computing modes for smart oceans.

The space–air–ground–sea integrated networks hold the potential for enabling the development of smart oceans by integrating the functionalities of the space layer, the air layer, and the ground layer [4]. Specifically, the satellites in the space layer can provide wide coverage and emergency communication services for marine objects in remote oceans. Thanks to the flexibility and mobility, these unmanned aerial vehicles (UAVs)/airships/balloons in the air layer can offer real-time communication and computing services for sea surface nodes. With powerful computing and storage capacities, these offshore base stations (BSs) deployed on the ground can support a large number of computing tasks offloaded by the marine objects. Therefore, the design and collaboration of the space–air–ground–sea integrated networks are the promising network framework to promote the development of smart oceans.

The multilayer hybrid networks for smart oceans provide an efficient prospect to enhance the ocean capacities. However, in consideration of the characteristics of multilayer hybrid networks, the open environment and time-varying topology cause the smart oceans to face some critical challenges (e.g., energy efficiency, network security, data privacy, etc.). Specifically, these underwater sensor nodes (USNs) deployed at the seabed are generally powered by batteries, which significantly influence the endurance for data collection. The energy consumption of underwater data transmission through acoustic transmission is larger than the computing overheads, and the batteries cannot be conveniently recharged owing to the limitations of seawater environments. It is necessary to design efficient energy-harvesting and transferring approaches to prolong the lifetime of USNs. Moreover, the underwater acoustic transmission suffers from long propagation delay and high packet loss probability, which degrades the communication efficiency [5]. Furthermore, a large number of valuable ocean data are collected, uploaded, and then processed; however, the data security and privacy may be destroyed by the malicious nodes in marine environments. It is still an important problem to pay attention to the security and privacy issues of ocean data collection and transmission.

There exist some works investigating the design and implementation of smart oceans. For instance, Yu et al. [6] proposed a crowdsourcing privacy protection scheme to enhance privacy protection in the data sharing of smart oceans. In [7], Hu et al. presented a secure data collection, transmission, and storage scheme in a smart ocean to resist the single point failure attack. In [8], Fang et al. investigated a heterogeneous autonomous underwater vehicles (AUVs)-aided information collection system by optimizing the AUV trajectory and resource allocation, with the objective of maximizing the energy efficiency of marine nodes. In [9], Alfouzan proposed an energy-efficient collision avoidance scheme for underwater sensor networks. In [10], Luo et al. summarized the recent air/water cross-boundary communications for underwater sensor networks. In [3], Zhou et al. exploited an energy-efficient routing protocol for underwater wireless sensor networks (UWSNs). The above works investigated the privacy, security, and energy-efficiency issues in ocean environments and proposed different solutions to address the problems under investigation. However, the integrated sensing, communication, and computing networks (ISCCNs) for smart oceans should be further discussed.

1.2. Existing Surveys

There have been many survey papers investigating the UAV networks, space–air–ground integrated networks (SAGINs), and satellite/air–ground networks. These works have exploited the fundamental network architecture, network security, and applications. For instance, in [11], Mozaffari et al. provided the potential benefits and applications forUAV-enabled wireless networks. In [12], Hayat et al. surveyed the characteristics and requirements of UAV networks for envisioned civil applications. In [4], Guo et al. reviewed the security threats for the space–air–ground–sea integrated networks. In [13], Wang et al. exploited the secure applications for the SAGINs–Internet of Things (IoT).

In [14], Zhang et al. reviewed the air–ground integrated mobile edge networks. In [15], Wei et al. investigated the demand for the satellite–terrestrial maritime communication networks. Table 1 summarizes the comparisons between our paper and previous relevant surveys; however, a comprehensive survey on the ISCCNs for smart oceans has not yet been investigated.

Table 1. Comparison of existing surveys and our work.

Network Feature	Reference	Main Contributions
UAV networks	[11]	Reviewed the fundamental tradeoffs in UAV-enabled wireless networks.
	[12]	Reviewed the general UAV networking related requirements and characteristics.
Space–air–ground integrated networks (SAGINs)	[4]	Reviewed the state-of-the-art of security issues for SAGINs.
	[13]	Reviewed the promising blockchain-based solutions for SAG–IoT security.
Satellite/air–ground networks	[14]	Reviewed the UAV-assisted air-ground integrated mobile edge networks.
	[15]	Reviewed the communication demand in satellite-terrestrial maritime communication networks
Satellite–air–sea integrated networks for smart oceans	Our work	Surveyed the architecture of the ISCCNs for smart oceans from four domains and five aspects and provided the state-of-the-art marine sensing, communication, and computing paradigms for smart oceans.

1.3. Motivations and Contributions

Although existing surveys have presented the hybrid network architecture related to satellite networks, aerial networks, terrestrial networks, and oceans networks, they all have common limitations. In particular, these works mainly focus on the integration of two-tiered segments such as air–ground network and satellite–terrestrial network, three-tiered segments such as SAGINs, and four-tiered segments such as satellite–air–sea integrated networks. However, the ISCCNs for smart oceans are not fully discussed.

In this paper, we conduct a comprehensive survey for the ISCCNs in smart oceans from the aspects of network architecture, key technologies, challenges, and solutions. The main contributions of this work are summarized as follows.

- We investigate the architecture of the ISCCNs for smart oceans from four domains (i.e., the satellite layer, the aerial layer, the sea surface layer, and the underwater layer) and five aspects (i.e., sensing-related, communication-related, computation-related, security-related, and application-related).
- We provide the key technologies of the ISCCNs for smart oceans, including the state-of-the-art marine sensing, communication, and computing paradigms. We discuss the emerging challenges from security and energy-efficiency points of view in marine networks and provide potential solutions to guarantee the intelligent services.
- We introduce the emerging applications for the ISCCNs in smart oceans to promote marine services. We also discuss the potential research directions for future works in marine networks.

As illustrated in Figure 1, the remainder of this survey is organized as follows. Section 2 presents the framework of ISCCNs in smart oceans. Section 3 introduces the key technologies of ISCCNs for smart oceans. The challenges and potential solutions of ISCCNs for smart oceans are discussed in Section 4. Section 5 provides the applications and open research directions of ISCCNs for smart oceans. Section 6 closes this paper with conclusions. For convenience, important abbreviations used in this paper are listed in Table 2.

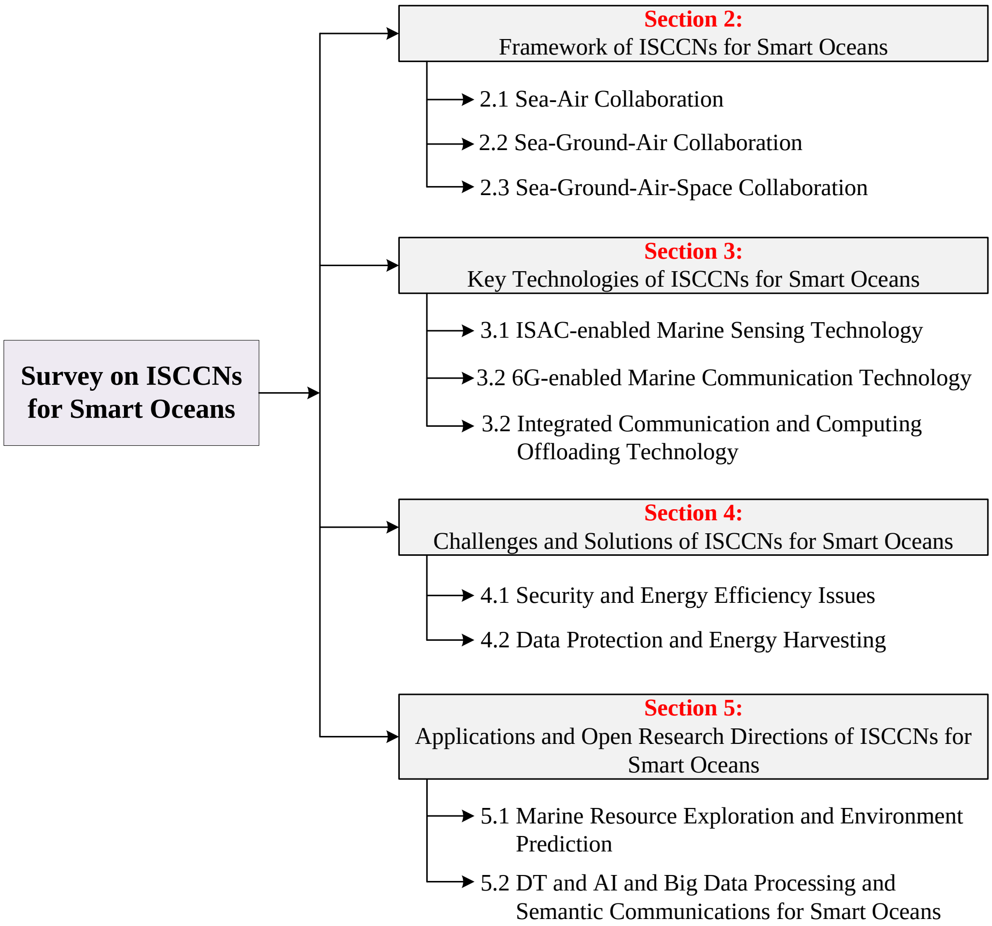

Figure 1. Organization of this paper.

Table 2. Summary of important abbreviations used in this paper.

Acronyms	Meanings	Acronyms	Meanings
AI	Artificial intelligence	NOMA	Nonorthogonal multiple access
AUG	Automatic underwater glider	OFDMA	Orthogonal frequency division multiple access
AUV	Autonomous underwater vehicle	QoS	Quality of service
BS	Base station	RF	Radio frequency
B-UAV	Bottom-UAV	RL	Reinforcement learning
CET	Cloud–edge–terminal	RSS	Received signal strength
DT	Digital twin	SAGE	Space–air–ground–edge
EE	Energy efficiency	SAGIN	Space–air–ground integrated network
EOCA	Energy optimization clustering algorithm	SDN	Software-defined networking
FL	Federated learning	SN	Sink node
IoT	Internet of Things	SWIPT	Simultaneous wireless information and power transfer
IRS	Intelligent reflecting surface	TDMA	Time division multiple access
ISAC	Integrated sensing and communication	TENG	Triboelectric nanogenerator

Table 2. *Cont.*

Acronyms	Meanings	Acronyms	Meanings
ISCCN	Integrated sensing, communication, and computing network	T-UAV	Top-UAV
LSTM	Long short-term memory	UAV	Unmanned aerial vehicle
MEC	Mobile edge computing	UASN	Underwater acoustic sensor network
MEC3	Mobile edge communications, computing, and caching	USN	Underwater sensor node
M-IoT	Marine Internet of Things	USV	Unmanned surface vehicle
MWN	Maritime wireless network	UWSN	Underwater wireless sensor network
NDN	Named data networking	UWA-CSN	Underwater acoustic cooperative sensor network
NFV	Network function virtualization	WPT	Wireless power transfer

2. Framework of ISCCNs for Smart Oceans

Figure 2 shows the framework of the ISCCNs for smart oceans with SDN assistance, which includes the space layer, the aerial layer, the sea surface layer, and the underwater layer. Specifically, the functionality of each layer is introduced as follows.

- *Space layer.* The space layer comprises diverse types of satellites, and the corresponding ground infrastructures, i.e., the ground/offshore BS and the control centers. The wide coverage characteristic of satellites guarantees the ubiquitous communication connection for smart oceans. In ocean disasters, satellites can provide emergency communication services in the deep sea. Moreover, these satellites are solar-powered, which enables the service endurance for marine objects.
- *Aerial layer.* The aerial layer consists of multiple aircrafts, UAVs, and balloons, which can establish the connections between marine objects and ground infrastructures, and can exchange information with the satellite layer. These UAVs deployed in the air can work separately or form a cluster to provide navigation, data relay, and computing services for ground/sea devices. Moreover, due to the high flexibility and the short distance between the aerial layer and sea surface layer, UAVs have the advantages of short response time and high throughput.
- *Sea surface layer.* The marine devices deployed at the sea surface layer can be vessels, unmanned surface vehicles (USVs), and buoys, which can collect the data from USNs and provide computing services for these resource-constrained maritime terminals through radio frequency (RF) transmission. Moreover, these marine devices in the surface layer can collect ocean environment information and complete harsh tasks. They can communicate with offshore BS and UAVs or offload workloads for processing.
- *Underwater layer.* A large number of USNs are deployed at the seabed for collecting oceanic data in the underwater layer. These USNs are generally powered by batteries, which cannot support data procession for a long time due to the difficulty of recharging in marine environments. The collected data are uploaded to the sea surface devices through acoustic transmission for storage and execution.

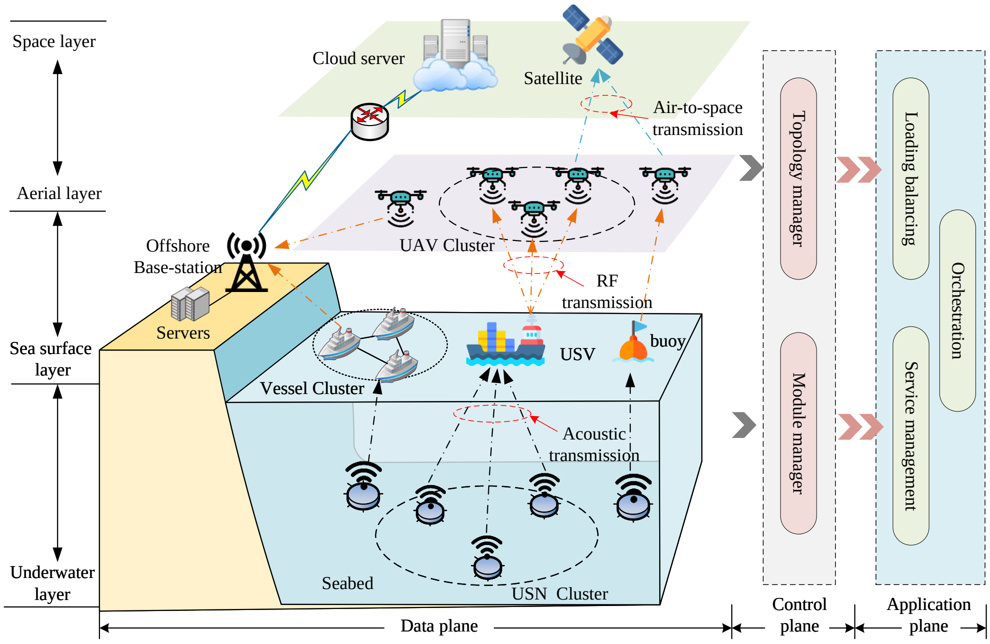

Figure 2. Framework of ISCCNs for smart oceans with SDN assistance.

The physical objects (e.g., satellites, UAVs, USVs, and USNs) in each layer can communicate with each other, and the connections and information exchange among the four layers can be established, which enables the collaboration of ISCCNs for smart oceans. To enhance the agility and resilience of ISCCNs and realize the unified architecture, standard, and management, the software-defined networking (SDN) technology, which consists of the application plane, control plane, and data plane, has the ability for programming ISCCNs via a logic controller. SDN provides a centralized configuration with on-demand services. Specifically, the data plane is responsible for perceiving and collecting data from physical objects in ISCCNs. The control plane comprises a large number of controllers for resource management (e.g., energy management and load balancing). The application plane supports types of application designs. Various services (e.g., navigation and content delivery) can be provided by the application plane to serve physical objects.

Based on the existing studies about multitier collaboration in marine networks, we divide the existing studies into three categories, i.e., two-tier for sea–air collaboration, three-tier for sea–ground–air collaboration, and four-tier for sea–ground–air–space collaboration. The details for two-tier for sea–air collaboration are presented in Section 2.1. Section 2.2 introduces three-tier for sea–ground–air collaboration, followed by four-tier for sea–ground–air–space collaboration in Section 2.3.

2.1. Two-Tier for Sea–Air Collaboration

The sea–air collaboration in a smart ocean exploits the communication and computing resource of devices deployed at the sea surface and aerially, e.g., USVs, buoys, vessels, and UAVs. The collaboration scenarios can be divided into "underwater-to-sea surface" and "sea surface-to-aerial". For instance, in [16], the authors employed USVs as marine data collectors for large-scale environment sensing in a remote ocean monitoring network, where a USV collects data from multiple monitoring terminals while avoiding collisions with monitoring terminals and obstacles. In addition, this paper formulated a trajectory optimization problem with practical constraints, including collision avoidance, steering angle, and velocity limitation, with the objective of minimizing energy consumption and data loss. A UAV-aided maritime data collection system with a fixed-wing UAV dispatched to collect data from marine buoys was studied in [17], with the objective of minimizing the UAV's energy consumption by jointly optimizing the communication time scheduling among the buoys and the UAV's flight trajectory subject to wind effect. In addition to two-tier collaboration for maritime data collection, the USVs and the UAVs can also provide the computing services for the resource-constrained marine terminals. In [18], an OFDM-based maritime broadband edge computing system model was developed to provide computing services to the surrounding USVs, and a USV energy consumption minimization problem was formulated by jointly optimizing the task offloading and resource allocation. In [19], the authors proposed a collaborative computation offloading scheme with the UAVs and the USV fleets in maritime communication networks. In [20], the authors studied the issue of computation task offloading for vessel terminals, with the objective of minimizing the energy consumption of vessel terminals and the execution delay of computation tasks.

In addition to the collaboration in the vertical direction in the above studies, there are also some studies investigating the collaboration in both vertical and horizontal directions. In [21], taking into account two transmission segments, i.e., underwater layer and air layer, a UAV-assisted multiaccess computation offloading for marine communication networks was proposed, with the objective of minimizing the energy consumption of ocean devices. In [22], an orthogonal frequency division multiple access (OFDMA)-assisted multiaccess edge computing offloading method for offshore scenarios was proposed, and a multiuser multihop unicast offloading model was established to alleviate the congestion of data unloading. In [23], the authors proposed a voyage-based computation offloading mechanism for the computation-intensive applications at sea, in which the edge nodes and the base stations are deployed on vessels to dynamically provide mobile edge computing services for nearby users to implement efficient computation offloading for secure maritime edge networks. In [24], a two-layer UAV maritime communication network with a centralized top-UAV (T-UAV) and a group of distributed bottom-UAVs (B-UAVs) was established, which aims to solve the latency minimization problem for both communication and computation in this maritime UAV swarm mobile edge computing (MEC) network. The above works investigated the framework for sea–air collaboration and proposed efficient schemes, which thus can enhance the communication and computation services for smart oceans.

2.2. Three-Tier for Sea–Ground–Air Collaboration

The sea–ground–air collaboration in smart oceans focuses on the integration of sea–edge–cloud to provide the communication and computation resource for marine IoT applications. In [25], the authors investigated the UAV-assisted data offloading for smart containers in offshore maritime communications, where the UAV acts as a relay node between smart containers and onshore BS. The mobility of the container vessel was considered in the offshore region and a UAV-assisted data offloading model was established. In [26], the authors presented the UAV-aided ocean monitoring network for remote oceanic data collection, in which monitoring data are transmitted first from battery-powered USNs to sea surface sink nodes (SNs) in a data collection cycle using underwater acoustic communication, and then a UAV hovering in the air collects all the data from SNs and relays them to a ground base station via wireless communication links. In [27], a maritime communication network framework was proposed, which combines the edge computing and center cloud to provide efficient computing capability for developing the ocean applications with different quality of service (QoS) requirements. In [28], the authors adopted the edge computing network architecture for maritime IoT, which migrates heavy-computation maritime applications to suitable servers by means of cloud–edge–end cooperation. In [29], the authors proposed an integrated satellite–maritime cloud–edge–terminal (CET) architecture, and considered the mobility of maritime vehicles in network resource management, including integrated transmission optimization, CET offloading, and proactive caching with resource-sharing marine edge clusters. Therefore, with the assistance of the aerial layer, the collaboration among sea–ground–air can further improve the communication and computing performance in smart oceans.

2.3. Four-Tier for Sea–Ground–Air–Space Collaboration

The feature of the sea–ground–air–space collaboration in smart oceans is the space layer, which involves the satellite communication with the consideration of the tough environment of the ocean. In [30], the authors proposed a space–air–ground–edge (SAGE) maritime communication network architecture which allows the underwater sensors to offload computing-intensive applications to the UAV edge servers in the marine environment. In [31], the authors introduced a space–air–ground–sea integrated network architecture with edge and cloud computing components to provide flexible hybrid computing services for maritime service. In this integrated network, the satellites and UAVs provide the edge computing and network access services. In [32], a heterogeneous space–air–ground–sea integrated network was adopted in the service-oriented maritime network, which adopts state-of-the-art technologies such as SDN, network slicing, and edge computing to construct an artificial intelligence (AI)-empowered digital twin for marine networks. The communication coverage can be enhanced by the satellites. Therefore, the integration among sea–ground–air–space promotes the communication and computing services for smart oceans.

2.4. Multitier Collaboration of ISCCNs for Smart Oceans

According to the studies on multitier collaboration of ISCCNs for smart oceans, Table 3 enumerates the classification of multitier collaboration of ISCCNs in smart oceans. Most existing studies focus on the two-tier collaboration for data collection and computing services (i.e., [16–24]), and few studies investigate the four-tier collaboration, which integrates the resources of the space–air–ground–sea (i.e., [30–32]). Thus, the space–air–ground–sea integrated network is still an open research direction in the future that can adopt the advanced technologies to provide intelligent services for marine applications. In the following section, we provide the key technologies of ISCCNs for smart oceans.

Table 3. Categories of multitier collaboration of ISCCNs in smart oceans.

Category	Ref.	Framework	Performance Metrics
Sea–Air	[16]	USN–USV	Minimize energy consumption and data loss
	[17]	Buoys–UAV	Minimize the energy consumption
	[18]	USV–USV	Minimize energy consumption
	[19]	USV–UAV	Minimize the overall execution time
	[20]	USV–EN	Minimize the energy consumption and delay
	[21]	USN–SN–UAV	Minimize the energy consumption
	[22]	USV–USV–EN	Minimize total delay
	[23]	USV–USV–Cloud	Minimize the total cost
	[24]	USV–UAV–UAV	Minimize latency

Table 3. *Cont.*

Category	Ref.	Framework	Performance Metrics
Sea–Ground–Air	[25]	USV–UAV–BS	Minimize average delay
	[26]	USN–USV–UAV	Maximize network lifetime
	[27]	USV–Edge–Cloud	Tradeoff between latency and energy consumption
	[28]	USV–Edge–Cloud	Minimize weighted energy consumption and delay
	[29]	USV–Edge–Cloud	Optimize the resource management
Sea–Ground–Air–Space	[30]	Space–Air–Ground–Sea	Computing services
	[31]	Space–Air–Ground–Sea	Hybrid computing services
	[32]	Space–Air–Ground–Sea	AI-empowered maritime network

3. Key Technologies of ISCCNs for Smart Oceans

3.1. ISAC-Enabled Marine Sensing Technology

In smart oceans, the sensing environment plays an important role in data collection. Recently, the integration of sensing and communication (ISAC) technology by integrating the radar system and communication system has attracted wide research interest, and can be adopted in smart oceans for data sensing and communication. By jointly designing the dual function of the radar sensing and communication in UAVs, ISAC empowered the traditional wireless communication system with the ability to "see" the ocean surroundings. In ISAC, the radar sensing signal and communication signal share the same frequency spectrum, which improves the spectrum efficiency and the throughput. Figure 3 provides an illustration of ISAC-enabled marine sensing in smart oceans, in which the ISAC base station has the abilities for both radar sensing and communication over the same spectrum channel. Moreover, the intelligent reflecting surface (IRS), which comprises a large number of reflecting elements, can enhance the performance of radar sensing. Thanks to the ISAC and IRS technologies, various marine environmental parameters (e.g., ship trajectories, water quality, temperature, turbidity, conductivity, dissolved oxygen, etc.) can be perceived for different applications. These marine environmental parameters are collected by the ISAC base station and then processed by the colocated edge servers. For instance, a marine fish farm monitoring system can be established to monitor water qualities. The collected information then informs the manager to make decisions. Ship trajectories can be detected for path planning and resource exploration in the ocean.

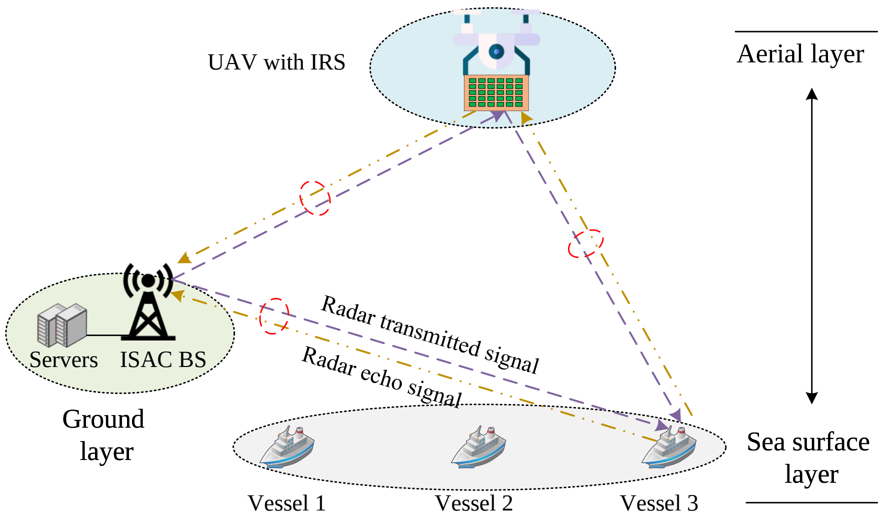

Figure 3. An illustration of ISAC-enabled marine sensing in smart oceans.

There are several studies which investigate UAV-enabled ISAC for marine aerial networks. Liu et al., in [33], proposed to offload the sensing data generated by the sensors on the vehicle to the edge server, with the assistance of UAV. An energy-efficient computation offloading strategy in the vehicular-to-everything networks was proposed in [33]. Meng et al., in [34], proposed a novel integrated periodic sensing and communication mechanism to achieve a critical tradeoff among the radar sensing and communication functionalities. The authors in [35] investigated the UAV-assisted ISAC, where multiple UAVs are equipped with dual-functional access points which transmit the composite signal of both the radar sensing and the communication functionalities. In [35], the transmit beamforming and the UAV trajectory were jointly optimized to maximize the average weighted sum-rate, meanwhile satisfying the requirement of the beampattern gain. The authors in [36] studied the UAV-assisted ISAC network where the UAV senses the target and offloads the data to the base station for analysis. In [36], the impact of the freshness of sensed data on the analysis accuracy was characterized by introducing the peak age of information. Moreover, the tradeoff between the radar sensing performance and the communication performance is challenging in the UAV-enabled ISAC for marine aerial networks. The authors in [37] utilized IRS to address the performance degradation due to the mutual interference between the radar sensing signal and data offloading transmission, and jointly optimized the IRS phase shift, the offloaded computation workloads, and the computation capacity allocation of the edge server. Since the processing and analysis of radar sensing data requires enormous computation resource, Ding et al., in [38], considered offloading radar sensing data generated by the ISAC terminals to the edge server for processing.

In addition to ISAC-enabled marine sensing technology, to improve the performance of marine network sensing and data collection, underwater wireless sensor networks have been established by deploying a large number of sensors on the seabed [39]. Moreover, an increasing number of marine wireless devices has been widely deployed, and these underwater sensor nodes can collect data from ocean environments and upload them to buoys or unmanned surface vehicles (USVs). Due to limited computing capacity, buoys and USVs can offload the workloads to a server center for further processing, which improves the computing efficiency.

3.2. 6G-Enabled Marine Communication Technology

With the growing increase of maritime activities, various ocean devices are deployed to collect oceanic data, which introduces high requirements for marine Internet of Things

(M-IoTs) with limited resources. In marine networks, there exist two transmission modes, i.e., the underwater transmission and the radio frequency transmission [26]. For underwater transmission, the acoustic transmission is leveraged as an effective approach for data transmission, since the radio frequency signal would suffer rapid attenuation in underwater transmission. These deployed underwater nodes collect oceanic data and then upload data to the surface nodes through acoustic links. Due to the complex ocean environment, the underwater acoustic transmission would suffer from low data rate and long propagation delay, which degrades the on-demand services. For radio frequency transmission, these surface nodes send their collected data to UAVs or offshore station for processing.

3.2.1. 6G-Enabled Marine Communications

By extending the concept of IoTs to marine networks, the coming 6G communication technology leads to the applications of M-IoTs with ultra-low latency and ultra-high speed, which is beneficial for exploring natural resources in the deep sea. Thanks to edge computing technology, marine 6G edge intelligence is an efficient paradigm to process massive ocean data to meet the requirements of different maritime applications. In maritime networks, by deploying computing nodes (e.g., offshore station, unmanned vehicles) at the edges of oceans, these delay-sensitive workloads can be processed with short response time. The integration of 6G and marine edge computing would provide ubiquitous services for emerging maritime applications such as ocean resource exploration, marine environmental monitoring, and marine disaster rescuing.

The 5G-enabled communication networks have received much attention from both academia and industry in recent years, and have been commercialized in maritime applications such as marine disaster rescue. However, 5G networks are unable to achieve the omnipotent extension of IoT. In sea surface transmission, the communication is based on radio frequency links. The 6G communication performance (e.g., ultra-high speed and ultra-low latency) can be guaranteed between sea surface nodes and offshore base stations/UAVs. The 6G-enabled marine wireless networks, which integrate hybrid satellite–terrestrial–marine communication networks, have gained much attention to promote the rapid development of M-IoTs. Many advanced studies are proposed to meet the performance requirements. A two-phase data-driven machine learning scheme was proposed [40] for vessel trajectory reconstruction, which promotes the intelligent vessel traffic services in 6G-enabled M-IoT systems. An edge computing network framework for M-IoTs based on the space–air–ground–sea integrated network of 6G was investigated [28] to enhance the energy efficiency. A cooperative coverage path planning method based on 6G-enabled cooperative autonomous underwater vehicles was studied [41] to balance the mission executions. A novel nonstationary 6G UAV channel model was proposed [42] for maritime communications to enhance the communication systems. In [43], the authors investigated the UAV-assisted maritime wireless communication to satisfy 6G requirements for ubiquitous wireless connectivity and extensive coverage. The main comparisons of 5G-enabled M-IoTs and 6G-enabled M-IoTs are summarized in Table 4.

Table 4. Comparisons of 5G-enabled M-IoTs and 6G-enabled M-IoTs.

Category	5G-Enabled M-IoTs	6G-Enabled M-IoT
Satellite Integration	N	Y
Service Objects	Connections for People and Maritime Things	Interactions for People and Maritime World
Traffic Capacity	10 Mbps/m^2	About 1–10 Gbps/m^3
Peak Data Rate	20 Gbps	$\geq$1 Tbps
Uniform User Experience	50 Mpbs 2D everywhere	10 Gpbs 3D everywhere

Table 4. *Cont.*

Category	5G-Enabled M-IoTs	6G-Enabled M-IoT
Latency	1 msec	0.1 msec
Energy/bit	Not Specified	1 pJ/bit
Localization Precision	10 cm on 2D	1 cm on 3D
Mobility Support	500 km/h	≥1000 km/h
Application Scenario	Maritime Internet of Things	Maritime Internet of Everything
	Support Underwater Communications	Efficient Underwater Communications
	Remote Deep Sea Navigation	Autonomous Deep Sea Navigation

3.2.2. IRS-Enabled Marine Surface Communications

In marine surface communications, due to the long distance between marine devices and the ground BSs, the channel conditions are often very weak. It is an important issue to enhance the channel conditions in marine networks. Thanks to their flexibility, UAVs bring significant advantages compared with the terrestrial communications, which can help an offshore BS establish a high-speed connection with these marine devices through adjusting its location or trajectory to enhance the data transmission performance. IRS technology, which comprises a larger number of reflecting metasurfaces, provides a promising paradigm to address this issue in marine networks [44]. By adjusting the phase shift of the metasurface, the incident signal can be manually controlled to enhance the desired signal and suppress the interference [45]. By deploying IRS on UAVs, the wireless channel can be enhanced by providing the additional reflecting link. IRS-enabled marine surface communications combine both the advantages of the flexible mobility of UAV and the capacity of IRS to reconfigure marine wireless propagation environments, which shows great potential in the 6G marine network.

Dong et al., in [46], investigated the UAV-enabled IRS-assisted IoT communication, jointly optimizing the UAV's trajectory and the deployment of IRS to minimize the energy consumption. In [46], the adaptive whale optimization algorithm and the elastic ring self-organizing map algorithm were introduced to compute the solutions. Xu et al., in [47], studied the master–auxiliary UAV-assisted IoT communication, where IRS is mounted on the UAV to improve the data transmission from the master UAV to the auxiliary UAV. In [47], a modified multiagent deep reinforcement learning algorithm, named preactivation penalty multiagent deep deterministic policy gradient, was proposed to maximize the sum rate. The authors in [48] utilized an UAV to extend the coverage of the IRS-assisted network, where the reliability of the connections with massive IoT devices was enhanced by adjusting the phase shifts of IRS. In [48], the achievable symbol error rate and the outage probability were derived as well as the bounds of the average performance of the signal-to-noise ratio. The authors in [49] investigated the coexistence of a legacy primary system and the secondary ambient backscattering system, whose performance was improved by an IRS-mounted UAV. Two technologies' applications for the IRS-enabled marine surface communications are provided as follows.

- *IRS-enabled marine surface communications can benefit from the simultaneous wireless information and power transfer (SWIPT) technology.* Leveraging the mobility of a UAV, the IRS on the UAV can be flexibly deployed to reinforce the SWIPT. Liu et al., in [50], studied the UAV-mounted IRS-assisted power transfer and information transmission in SWIPT, where different devices are scheduled by a time division multiple access (TDMA) protocol. Li et al., in [51], utilized IRS to enhance the channel to improve the coverage area of the UAV and the energy transfer efficiency via nonorthogonal multiple access (NOMA) transmission, by jointly optimizing the transmit power of the UAV, the successive interference cancellation decoding order, and the phase shift of the IRS. Mei et al., in [52], studied the downlink UAV-enabled IRS-assisted SWIPT system, where the charging process of the mobile devices and the data transmission are performed by leveraging the time switching mechanism. Yu et al., in [53], investigated the IRS-assisted SWIPT system, where multiple IRSs are deployed on UAVs and high buildings to improve both the performance of information transmission and energy transfer. In [53], the active beamforming on the transmitter, the phase shift of IRS, the power splittingratio, and the trajectories of UAVs are jointly optimized to maximize the average data rate.

- *IRS-enabled marine surface communications can also benefit from the NOMA technology, which allows marine devices to connect to the offshore BS*. Jiao et al., in [54], investigated the UAV-enabled IRS-assisted NOMA downlink transmission, where the rate of the user with good channel condition is maximized meanwhile the requirement of the rate of the user with bad channel condition can be satisfied. In [54], the position of the UAV, the active beamforming, and the phase shift of IRS are alternatively optimized via the successive convex approximation technique. Liu et al., in [55], analyzed the converge performance of multiple IRSs which were mounted on multiple UAVs, where a tier of UAVs served several devices via NOMA. The authors in [56] utilized IRS to assist the NOMA transmission in the scenario of multiple UAVs, where the users were divided into multiple NOMA clusters. The results in [56] showed that the interference of two UAVs can be reduced by adjusting their distance. The authors in [57] analyzed the outage probability and the ergodic spectral efficiency in the UAV-assisted NOMA transmission, where the IRS on the UAV served as a relay to assist the NOMA transmission. Cai et al., in [58], investigated the UAV-assisted NOMA network, utilizing IRS to reduce the overall energy consumption. The results in [58] illustrate that NOMA can provide more degrees of freedom in system design compared with the orthogonal multiple access scheme, and IRS helps to save the communication power of UAV.

The existing proposals of ISAC-enabled marine sensing technology and IRS-enabled marine surface communications in marine networks are discussed in Table 5.

Table 5. Existing proposals of ISAC-enabled marine sensing technology and IRS-enabled marine surface communications in marine networks.

Topic Focused on	Network Model	Ref.	Optimization Objective	Proposed Approach
ISAC-enabled marine sensing technology	Integrated periodic sensing and communication	[34]	System achievable rate	Two-layer penalty-based algorithm
	UAVs-enabled aerial dual-functional access points	[35]	Average weighted sum-rate throughput	Successive convex approximation and semidefinite relaxation
	IRS-assisted performance improvement	[37]	Energy consumption	Block coordinate descent and difference-convex programming
	ISAC-assisted data offloading	[38]	Energy consumption	Block coordinate descent
IRS-enabled marine surface communications	UAV-enabled IRS-assisted IoT communication	[46]	Energy consumption	Adaptive whale optimization algorithm and elastic ring self-organizing map algorithm
	IRS-assisted master–auxiliary UAV network	[47]	Total throughput	Preactivation penalty multiagent deep deterministic policy gradient
	UAV-assisted IRS for SWIPT	[50]	Minimum average achievable rate	Successive convex approximation and block coordinate descent
	NOMA and energy harvesting model	[51]	Achievable sum-rate maximization	Successive convex approximation penalty function method and difference-convex programming

3.3. Integrated Communication and Computing Offloading Technology

In marine seabeds, lots of USNs are deployed to monitor ocean environments. These collected data are uploaded to USVs through acoustic links. At the sea surface, USVs sailing on the sea can collect or receive data from USNs. In the aerial layer, UAVs have high flexibility and mobility which can be easily and quickly deployed over the sea. Using short-range LoS communication links, UAVs can support computing services as the aerial base stations. In [59], the authors proposed a hybrid satellite–UAV–terrestrial network for 6G ubiquitous coverage, with the objective of minimizing the total energy consumption. In [60], the authors investigated the computing architecture of SAGINs from the characteristics of each network segment and the computing interactions among different network segments. In [61], the authors investigated UAV-assisted mobile edge communications, computing, and caching (MEC3) schemes to reduce the system latency. To further improve the efficiency of offloading transmission, many advanced technologies for enabling spectrum-efficient yet massive-connectivity transmission, e.g., NOMA, have been leveraged for multiaccess computation offloading [62–64]. In [27], the authors investigated the tradeoff between latency and energy consumption in low-cost, large-scale maritime communication, with the objective of optimizing the resource allocation under limited energy and sensitive latency.

In marine networks, huge amounts of ocean data need to be processed. The traditional marine communication networks adopt the centralized cloud computing framework, in which the data storage and processing are executed in the cloud data center. However, offloading computation workloads to remote cloud servers may place high pressure on the backbone networks and bring inevitable long delay, and the network resources of marine communications are limited, which affect the real-time service performance. Multiaccess edge computing has been envisioned as an essential technology for marine networks that allows ocean devices to offload their workloads to different edge computing servers simultaneously. Thanks to NOMA transmission technology, it has been envisioned as an efficient multiple access approach for enabling massive connectivity in maritime networks. Specifically, NOMA enables ocean devices to reuse the same resource block for data transmission, which improves the channel efficiency and transmission throughput in maritime networks. Ocean devices can form the NOMA cluster for data transmission and procession.

Existing works have investigated multiaccess edge computing in marine networks. Specifically, an NOMA scheme between sea surface nodes and UAV transmissionfor data collection was studied [26], with the objective of minimizing the transmission delay. An NOMA-based maritime UAV communication scheme was exploited [65] to maximize the minimum ship throughput by formulating a joint transmit power and transmission duration allocation problem. In [66], the authors studied an NOMA-based hybrid satellite–UAV–terrestrial maritime network for on-demand coverage to maximize the sum rate of the system. In [67], the authors exploited the seamless and reliable demand for communication and computation in maritime wireless networks. In [68], the authors presented a software-defined maritime fog computing architecture to provide localized services for maritime devices. In [69], the authors investigated the IRS-aided wireless inland ship MEC network architecture to support USVs' communication and computation, with the objective of minimizing the network energy consumption. Existing proposals of integrated communication and computation offloading in marine networks are summarized in Table 6.

Table 6. Existing proposals of integrated communication and computation offloading in marine networks.

Topic Focused on	Solutions	Ref.	Proposal
Multiple access	NOMA transmission	[65]	NOMA-based maritime UAV communication model for maximizing the minimum ship throughput
	FDMA transmission	[70]	Single-carrier FDMA design for underwater acoustic communications
	OFDMA transmission	[22]	Multiaccess edge computing offloading based on OFDMA technology for alleviating the congestion of data unloading
	OFDM transmission	[18]	OFDM-based maritime broadband MEC system model for task offloading
Performance evaluation	Energy optimization	[71]	An improved energy optimization clustering algorithm for the multihop underwater acoustic cooperative sensor networks
		[72]	Energy-efficient image recognition system for ensuring a high recognition accuracy
	Delay optimization	[27]	Two-stage offloading optimization for energy–latency tradeoff in M-IoTs
		[73]	Shipping lane approach for optimizing the route selection in delay-tolerant routing
Resource allocation	Channel allocation	[74]	An energy-efficient channel allocation-based data aggregation
	Computing offloading allocation	[75]	Energy harvesting for MEC-enabled maritime task offloading
	Power allocation	[76]	QoS-guarantee power optimization for improving the NOMA transmission rate for each beam
	Task allocation	[77]	A novel task-allocation-scheme-based game theory for smart ocean IoT

4. Challenges and Solutions of ISCCNs for Smart Oceans

4.1. Challenges of ISCCNs for Smart Oceans

Different from the traditional cloud computing, MEC technology enables marine objects to offload tasks to the edge of marine networks. However, since most edge devices (e.g., UAVs and USNs) are manufactured using more economical circuits, this class of devices is more vulnerable to attack. Considering the vulnerability of marine devices, it is critical to protect the data security and privacy for MEC. Recently, there have been a lot of studies investigating the data security and privacy of MEC, including the data confidentiality and data integrity [78–80].

4.1.1. Data Confidentiality

As a fundamental requirement in the marine networks, the data confidentiality requires that the data cannot be read by any unauthorized and unlawful user. To enhance the data confidentiality, the encryption theory is exploited by many studies. Generally, with the encryption technology, the data are first encrypted before being sent to the target user. The target user needs to decrypt the data using a decoding method that is jointly specified with the sender. In [81], Feng et al. proposed an attribute-based encryption model with parallel outsourced decryption to address the response time requirement of edge intelligent networks. In [82], Liu et al. proposed a multikeyword attribute-based searchable encryption scheme through cloud–edge coordination to address the issue of the large computing overhead of the existing attribute-based searchable encryption. In [83], Wu et al. proposed a differential aggregation encryption model to ensure the security of terminal data. In [84], Hu et al. proposed a privacy protection strategy based on homomorphic encryption to prevent the privacy of user data from being leaked during the wireless channel propagation process and relay forwarding. In addition to the encryption technology, there are also some other technologies to enhance the data confidentiality of MEC. In particular, due to the potential advantages, the cooperative jamming scheme [85,86] and federated learning (FL) [87] have attracted a lot of interests. We introduce these two technologies in detail in Sections 4.2.1 and 4.2.2.

4.1.2. Data Integrity

Data integrity refers to ensuring that data are not maliciously damaged or modified during data transmission or storage. Specifically, the adversary can violate the data integrity through intervening attacks or relay attempts. Thus, there are many studies focusing on the solutions for addressing the data integrity violation. In [88], Cui et al. proposed an inspection and corruption localization scheme for edge data integrity, and theoretically proved its correctness and probabilistic integrity guarantees. In [89], Li et al. proposed an approach for app vendors to inspect the integrity of their edge data replicas across edge servers and localize corrupted ones. In [90], Yu et al. exploited a data-time sampling strategy for data integrity checking in decentralized storage. In [91], the authors investigated a data integrity auditing scheme that guarantees sure data sharing with sensitive information hiding. In [92], Tong et al. proposed a remote data integrity checking protocol for edge storage, and an extended protocol for efficient batch verification of multiple edges. In addition to the above traditional methods, blockchain [93,94] has been developed as another promising technology based on linked data structure to enhance the data integrity, which will be introduced in Section 4.2.3.

4.1.3. Energy Efficiency

With the unprecedented growth of ocean applications, e.g., ocean exploration, environment monitoring, etc., these marine activities introduce high requirements for energy efficiency of marine devices. It is necessary to establish the low-cost marine networks to enhance the endurance of marine devices. There exist many works investigating the energy efficiency in marine networks. Specifically, in [95], the authors investigated the collaborative relay communication in distributed maritime wireless networks (MWNs) to maximize the energy efficiency (EE) for resource allocation. In [96], the authors proposed an energy-efficient probabilistic depth-based routing for underwater sensor networks (UWSNs) to save energy consumption. In [97], an adaptive deep Q-network-based energy- and latency-aware routing protocol was proposed to reduce network overhead. In [71], an improved energy optimization clustering algorithm (EOCA) was exploited for the multihop underwater acoustic cooperative sensor networks (UWA-CSN), with the objective of adaptively controlling the energy consumption of data transmission for each hop. In [98], the authors investigated the dynamic clustering K-means algorithm to cluster the underwater sensor nodes, with the objective of minimizing the overall energy consumption of the system. In [99], the authors studied the deployment of underwater acoustic sensor networks (UASNs) on the named data networking (NDN) to explore the energy consumption performance. In [100], an energy-efficient mobile data collection scheme based on node cooperation protocol was proposed in an underwater acoustic sensor network. In [101], the energy allocation in underwater acoustic nodes powered by energy harvesting was presented to maximize the expected total amount of delivered data over finite time slots.

4.2. Solutions of ISCCNs for Smart Oceans

4.2.1. Cooperative Jamming for Security

Due to the broadcast nature of wireless networks, the malicious nodes can capture the edge device's transmission signals and decode them in a brute-force manner when the edge users offload their computation workloads to the edge server. In particular, in the marine edge computing networks, when the USNs offload the computation workloads to the USVs and the USVs forward the computation workloads to the UAVs, their transmission is able to be eavesdropped on by some eavesdroppers on the underwater layer, sea surface layer, or the aerial layer. As a result, to counter the eavesdropping attack, physical layer security is an efficient method to guarantee the secrecy demands from the perspective of information theory. During the offloading period of marine devices in MEC, the marine helper devices can send artificial noise to the eavesdropper to degrade the overhearing capacity of the eavesdroppers, while increasing the secrecy offloading throughput. Through ingenious design, cooperative jamming can theoretically realize the confidentiality of computation offloading even though the eavesdroppers have significant computational power. In [102], Zhang et al. proposed a cooperative jamming lightweight mechanism based on MEC to prevent eavesdropping attacks for the random mobile nodes in industrial wireless networks. In [103], Qian et al. investigated the secrecy-based MEC via NOMA transmission and optimized the selection of the wireless devices for cooperative jamming to reduce the total energy consumption. In [104], Li et al. utilized the cooperative jamming between NOMA user pairs to offload tasks in two time slots securely. In [105], Cui et al. proposed a fountain-coding-based strategy combined with cooperative jamming for secure service migration in MEC.

4.2.2. Federated Learning for Data Privacy

In traditional distributed machine learning, data of all participants need to be gathered together first, and then used by the central server to train the AI network. A significant issue of the above paradigm is that data sharing leads to the disclosure of participants' privacy. To address the issue, a novel paradigm of distributed machine learning, i.e., FL, provides a promising solution [106–108]. Different from traditional distributed machine learning, FL does not require the participants to share their data. Therefore, in the framework of FL, the marine client devices do not offload their data to servers, and they train the local models using the raw data and only upload the trained models to servers, which protects the data privacy. In particular, as shown in Figure 4, in FL, each USV individually trains the global model received from the UAV server with its own dataset to update the local model, and then sends the updated local model to the UAV server. The UAV server aggregates all the local models received from the participants to update a new global model and broadcasts the updated global model to the participants. The iterative training is terminated until the AI model meets the accuracy requirement. Assisted by FL, in MEC, when the edge users collaborate to generate an AI model, they are not required to offload their data to the edge server. In addition, compared to transmitting a large amount of raw data, only uploading model parameters to the edge server saves communication resources significantly. Considering the potential advantages of FL, there have been many studies investigating the application of FL to MEC. In [109], Bao et al. proposed an MEC-based joint FL client selection scheme for vehicular networks. In [110], Zhou et al. proposed a differentially private FL model against poisoning attacks for MEC deployment. In [111], Mills et al. proposed a multitask FL algorithm for personalized deep neural networks in MEC. In [112], He et al. designed a privacy-preserving and low-latency scheme in MEC to address the privacy threats. In [113], Zhang et al. proposed an FL-based MEC platform for cyberphysical systems. In [114], Ye et al. proposed optimization algorithms for FL based on MEC to tackle the issue of large computational cost in mobile devices. In [115], Ahmed et al. proposed a federated transfer learning model for heterogeneous MEC. In [116], Amannejad et al. proposed an automated solution of building and evaluating FL models for MEC. Existing proposals of FL for air–sea integrated networks are summarized in Table 7.

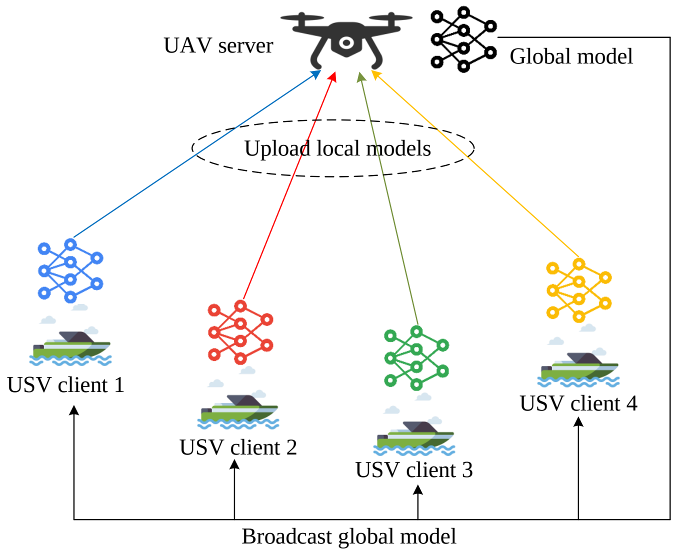

Figure 4. An illustration of FL for data privacy in smart oceans.

Table 7. Existing proposals of FL for air–sea integrated networks.

Topic Focused on	Purpose	Ref.	Proposal
FL for aerial networks	Counter potential security and privacy threats	[117]	Propose a secure FL framework for UAV-assisted mobile crowdsensing
	Predict the air quality index accurately and timely	[118]	Propose a new FL-based aerial–ground air quality sensing framework
	Improve the reliability and efficiency of data sharing	[119]	Develop an asynchronous FL framework for multi-UAV-enabled networks
	Mitigate resource consumption for UAVs and user devices	[120]	Propose deep-reinforcement-learning-based framework to enable sustainable FL with energy-harvesting user devices
	Realize the dynamic resource allocation	[121]	Design an FL-based multiagent method for realizing information interaction and combined dispatching in UAV networks
	Address jamming attack detection in flying ad hoc network	[122]	Propose an FL-based on-device jamming attack detection security architecture for flying ad hoc network
FL for marine networks	Solve the problem of worker selection in FL	[123]	Propose a secure sharing method for M-IoT under an edge computing framework based on FL
	Address multiagent cooperation and privacy protection issues	[124]	Propose a part-FL scheme combining the advantages of FL algorithm and split learning algorithm
	Diagnose device failures in Internet of Ships	[125]	Design the Paillier-based communication scheme to encrypt the transmission parameters in Internet of Ships
	Predict the ships' positions securely	[126]	Propose a new cooperative collision avoidance system based on FL for inland ships at MEC level

4.2.3. Blockchain for Data Integrity

Using technologies such as cryptography and consensus mechanisms, blockchain subdivides data into shared blocks linked together with unique identifiers in the form of cryptographic hashes, and thereby creates a peer-to-peer storage network for large amounts of data. Blockchain provides more secure data storage due to its encryption and common authentication mechanisms [127]. Specifically, data cannot be altered without the verified permission of a sufficient number of legal marine devices. Once a marine device attempts to change the data, all nodes in the blockchain are aware of the action. Therefore, blockchain can effectively prevent fraud and data tampering. Due to the advantages of blockchain in terms of the data integrity, a lot of studies focus on the exploitation of blockchain in MEC. In [128], Yuan et al. proposed a decentralized system to support and drive collaborative edge storage based on blockchain. In [129], He et al. proposed a general framework for blockchain-based MEC-enabled IoT scenarios and designed a smart contract within a private blockchain network. In [130], Ni et al. studied the design method of using blockchain for safe and efficient resource sharing in the context of 6G, which can be used in MEC by balancing the impossible triangle of blockchain. In [131], Guo et al. proposed a resource management scheme for mobile blockchain in MEC. In [132], Guo et al. proposed a distributed and trusted authentication system with blockchain and MEC. In [133], Wu et al. identified and addressed key challenges of task offloading in blockchain-enabled heterogeneous IoT–MEC environments. In [134], Sheng et al. constructed a near-online tracking framework with co-occurrence constraints for blockchain-based MEC.

4.2.4. Energy Harvesting and Energy Transfer

In marine information services, marine nodes are generally powered by limited resources such as battery and oil; the limited lifetime of marine nodes is the critical challenge for implementing marine applications. Through energy harvesting, these marine devices can harvest energy from solar or water waves, which can enhance the endurance of marine devices for sensing and data collection. Network resource allocation plays an important role in designing energy-harvesting wireless sensor networks, and researchers have focused on designing energy-saving techniques to minimize the energy consumption in marine networks. Specifically, in [135], the authors developed a prototype of the energy-harvesting unit and the wireless communication unit for self-sustaining broadband long-range maritime communication. In [136], the authors proposed an energy-efficient routing protocol through energy-harvesting intelligent relay selection protocol in UWSNs. In [137], the authors investigated a received signal strength (RSS)-based localization framework for energy-harvesting underwater optical wireless sensor networks, in which these sensor nodes with insufficient battery harvest ambient energy and start communicating once they have sufficient storage of energy. In [138], the optimal power allocation problem is proposed to maximize the long-term end-to-end sum rate of an underwater full-duplex energy-harvesting relay network. In [139], the authors presented a novel localization technique for energy-harvesting hybrid acoustic–optical underwater wireless sensor networks. In [140], a contact-separation mode triboelectric nanogenerator (TENG) was exploited to create an efficient energy harvester to transform the mechanical energy of vibrating pipes into electrical energy. In [141], the authors proposed an undersea wireless power and data transfer system with the shared channel, in which the power and data can be transferred with the same channel based on the time-division multiplexing theory. In [142], the authors proposed a wireless power transfer (WPT) system to address the voltage difference between the generated power and the energy storage system power. In [143], the authors exploited the wireless power transfer systems and presented a coil structure utilizing two transmitter coils placed symmetrically adjacent to each side of the receiver coil.

5. Applications and Open Research Directions of ISCCNs for Smart Oceans

5.1. Applications of ISCCNs for Smart Oceans

5.1.1. Marine Resource Exploration

Marine resource exploration and mining play a vital role in the sustainable development of smart oceans. The traditional method for marine resource exploration is to deploy ships, observation stations, marine buoys, etc., to obtain marine environment data. However, this approach is generally high in cost, long in duration, and limited in scope, which makes it difficult to achieve large-area and real-time ocean observations. The emerging space–air–ground–sea integrated networks have the potential to improve the efficiency and effectiveness for marine resource exploration. ISCCNs can obtain the marine data (e.g., water quality, turbulence, coral reef) in real time for resource exploration and decision-making. Specifically, the huge data streaming collected by UWSs can be uploaded to the ground layer, the aerial layer, or the space layer for processing and analyzing. The advanced 5G and the coming 6G communication technology can enhance the throughput of marine communications, and the results will be transferred to the observation station. Researchers have proposed some works to improve the performance of resource exploration. In [144], Huang et al. proposed an implementation scheme of a marine wireless sensor network monitoring system, in which the collected data were sent to the server visualization platform for analysis. In [145], a control model based on artificial neural network was proposed to improve the control effect of the marine resource exploration through artificial neural network. In [146], Zhao et al. investigated the fundamental geological conditions of deep marine carbonate reservoirs for the higher-than-expected resource potential therein. In [147], Liu et al. exploited the safety analysis of shrinkage monitoring equipment in marine resource exploration. In [148], Pan et al. studied the autonomous learning model of the learning robot for marine resource exploration based on the adaptive neural network controller.

5.1.2. Marine Environment Information Prediction

Marine information and services are the basis for human society to understand and develop the ocean, and include marine information detection and collection, marine information dissemination and networking, marine information processing and fusion, marine information application services, etc. The marine environment has the characteristics of dynamic, three-dimensional, and fuzzy. Through visualization of marine environmental data, ISCCNs enable us to query, count, and forecast marine environmental information, thus providing fast and intuitive decision-support information. The recent advances in computing capability and big data processing technology will lead to a big development in ocean data visualization. However, the visualization of ocean information implies the need for faster and more accurate ocean information collection techniques. Therefore, the adoption of 6G network technology in the marine environment is an unstoppable trend. There have been many studies investigating the marine information and service prediction. In [149], Lyu et al. proposed a mother-ship-assisted cooperative transmission scheme to mitigate the impact of limited resources and path loss on the estimation performance. In [150], Zeng et al. established the systematic USV kinetics and information transmission models, and maximized the minimum expected throughput over allships by jointly optimizing the trajectory and communication resource allocation. In [151], Arienzo et al. proposed a cognitive-relay-based architecture to enhance the data transmission by increasing the throughput and the real-time reception capacity, which was shown to enhance the current maritime surveillance systems. In [152], Yang et al. proposed a novel SAGE integrated maritime network architecture to offload computation-intensive IoT services at sea, significantly reducing offloading latency and weighted latency–energy costs. In [153], Duan et al. proposed a cooperative multicast communication scheme for maritime users relying on joint beamforming optimization and relay design to increase the throughput and the energy efficiency.

5.2. Open Research Directions of ISCCNs for Smart Oceans

5.2.1. Digital Twin for Smart Oceans

Digital twin (DT) plays an important role in marine networks for creating the real-time digital simulation models of marine objects in the digital space, thus realizing the communication, cooperation, and information sharing, and supporting the decision-making in smart oceans [154,155]. Moreover, DT has the ability to predict future events by continuously estimating and analyzing the real-time state in marine networks. Several works have explored utilizing DT to enhance the performance of marine communication networks. In [156], Dai et al. studied the DT-envisioned secure federated aerial learning for air–ground integrated networks via an aerial blockchain approach. In [157], Fan et al. proposed a DT-empowered MEC architecture to train the lane-changing strategy with the deep reinforcement learning approach. In [158], the authors studied the end-to-end latency minimization issue of DT-aided offloading in edge networks supported by multiantenna UAVs under the strict constraints of ultra-reliable low-latency communication links. In [159], the authors investigated FL-assisted DT edge networks and formulated an optimization problem to reduce the communication costs. However, most of these studies remain in the application of aerial networks and ground networks.

In [160], Liu et al. explored the safety performance of the maritime transportation system based on DT, aiming to promote the development of intelligent and digital maritime transportation. In [161], Wen et al. established a DT of multi autonomous underwater glider monitoring tasks, which improved the independent monitoring capability of marine equipment. At present, DT still lacks research in the field of marine networks. Inspired by DT's application in aerial and ground wireless networks, such as maritime navigation, maritime disaster prediction, maritime emergency rescue, and maritime real-time tracking and positioning, other marine applications have the opportunity to mature. It can be predicted that the construction of smart oceans can be further improved under the promotion of DT. These bring more possibilities to the application of DT in marine networks and the construction of intelligent aerial and marine networks.

5.2.2. Artificial Intelligence for Smart Oceans

As marine networks continuously incorporate different devices, the heterogeneity of marine networks becomes a great challenge. Therefore, the future marine network should have strong adaptiveness in order to efficiently adapt to different devices and protocols. Moreover, unlike traditional terrestrial networks, the energy capacity of marine and airborne devices is severely limited. In order to solve the energy limitation problem of marine network equipment, one way is to improve the efficiency of energy utilization through resource optimization, and another way is to improve the energy reserve of equipment through energy harvesting. Another difference with terrestrial networks is that due to the complexity of the marine environment, the equipment is more fragile and is difficult to repair in time. Therefore, the marine network should be more robust, especially in case of failure of some equipment nodes.

In addition to the above research directions, another feature of the future marine networks is that more artificial intelligence techniques are exploited to improve the performance of the marine networks. Recently, there have been many studies investigating the artificial intelligence used in marine networks, e.g., reinforcement learning (RL), transfer learning, and metalearning. In [162], Sun et al. developed an underwater image enhancement framework based on reinforcement learning. In [163], Wang et al. proposed a data-driven performance-prescribed reinforcement learning control scheme for the unmanned surface vehicle system. In [164], Cheng et al. proposed a supervised transfer-learning-based framework for sea state estimation. In [165], Zurowietz et al. proposed a method for unsupervised knowledge transfer to improve the performance of marine object detection. In [166], Guo et al. proposed a few-shot classification model based on transfer learning for marine plankton images. In [167], Zhang et al. proposed a metalearning method for few-shot classification of aerial scene images.

5.2.3. Big Data Processing for Smart Oceans

Smart oceans produce a large amount of oceanic cognitive big data which can be developed into various maritime applications, such as maritime navigation, maritime disaster prediction, maritime emergency rescues, and maritime real-time tracking and positioning. To further exploit the oceanic big data and improve the performance of the corresponding applications, the state-of-the-art software-defined networking (SDN) and network function virtualization (NFV) technologies can provide promising solutions in different aspects [168]. In [169], the SDN and edge computing were employed to support the interoperability of heterogeneous maritime networks and provide a deep understanding of maritime network connectivity characteristics and edge capabilities. In addition to the SDN technology, a blockchain-enabled framework was investigated in [170] for analysis of real-time maritime data at the edge of the networks while meeting the security and privacy issue of maritime transportation systems. Moreover, a new generation of artificial intelligence wireless communication technology in marine monitoring platforms was studied in [171], and a reinforcement-learning-based trajectory optimization was adopted to effectively increase the coverage of the trajectory of the automatic underwater gliders (AUGs). Thus, more advanced network protocol technologies, e.g., network slicing, can be applied to manage the maritime resource and provide the various intelligent computing services for marine networks. Moreover, the deep-learning-based methods, e.g., long short-term memory (LSTM) and reinforcement learning, can be used to solve the time-dependent prediction tasks in marine networks and provide intelligent task-scheduling strategies.

5.2.4. Semantic Communications for Smart Oceans

In marine networks, the communication channels often suffer from low bandwidth and high latency due to the characteristics of acoustic transmission technology. The fast-growing amount of data in marine networks calls for a new communication paradigm to support efficient data transmission for the smart ocean. Semantic communication is an emerging communication technology that aims to extract and deliver the semantic information of the data [172]. In semantic-aware marine networks, the irrelevant information of the sensing data can be filtered out before transmission, which can significantly save the bandwidth and reduce the latency of the communication links [173]. Unlike classical communication systems, semantic-based transmission technology may rely on prior knowledge (e.g., deep learning model) to extract the compact and accurate information of the data. This imposes new challenges on how to train comprehensive semantic extraction models for diversity application in marine networks. In addition, the on-device inference of the extraction model raises intensive computation overhead for USNs. To tackle these issues, future work may focus on employing transfer learning and domain adaption to improve the performance of semantic-aware marine networks [174]. Moreover, computation-efficient management methods and lightweight deep learning models should be investigated to enhance the resource utilization for the on-device semantic extraction [175].

6. Conclusions

In this paper, we conducted a comprehensive survey on the ISCCNs for smart oceans. Specifically, we exploited a collaborative framework based on space–air–ground–sea integrated networks from four domains (i.e., the space layer, the air layer, the ground layer, and the sea layer) and five aspects (i.e., sensing-related, communication-related, computation-related, security-related, and application-related). Next, we presented the key technologies and the state-of-the-art integrated communications and computing in smart oceans. Then, we discussed the challenges in smart oceans from the point of view of security and energy-efficiency issues, and provided potential solutions to guarantee the intelligent services in marine networks. Finally, we introduced the emerging applications in smart oceans, and discussed some future research directions in smart oceans.

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References

1. Qiu, T.; Zhao, Z.; Zhang, T.; Chen, C.; Chen, C.P. Underwater Internet of Things in smart ocean: System architecture and open issues. *IEEE Trans. Ind. Inform.* **2019**, *16*, 4297–4307. [CrossRef]
2. Zolich, A.; Palma, D.; Kansanen, K.; Fjørtoft, K.; Sousa, J.; Johansson, K.H.; Jiang, Y.; Dong, H.; Johansen, T.A. Survey on communication and networks for autonomous marine systems. *J. Intell. Robot. Syst.* **2019**, *95*, 789–813. [CrossRef]
3. Zhou, Z.; Yao, B.; Xing, R.; Shu, L.; Bu, S. E-CARP: An Energy Efficient Routing Protocol for UWSNs in the Internet of Underwater Things. *IEEE Sens. J.* **2016**, *16*, 4072–4082. [CrossRef]
4. Guo, H.; Li, J.; Liu, J.; Tian, N.; Kato, N. A Survey on Space-Air-Ground-Sea Integrated Network Security in 6G. *IEEE Commun. Surv. Tutor.* **2022**, *24*, 53–87. [CrossRef]
5. Han, G.; Zhang, C.; Shu, L.; Rodrigues, J.J.P.C. Impacts of Deployment Strategies on Localization Performance in Underwater Acoustic Sensor Networks. *IEEE Trans. Ind. Electron.* **2015**, *62*, 1725–1733. [CrossRef]
6. Yu, Y.; Guo, L.; Liu, S.; Zheng, J.; Wang, H. Privacy Protection Scheme Based on CP-ABE in Crowdsourcing-IoT for Smart Ocean. *IEEE Internet Things J.* **2020**, *7*, 10061–10071. [CrossRef]
7. Hu, C.; Pu, Y.; Yang, F.; Zhao, R.; Alrawais, A.; Xiang, T. Secure and Efficient Data Collection and Storage of IoT in Smart Ocean. *IEEE Internet Things J.* **2020**, *7*, 9980–9994. [CrossRef]
8. Fang, Z.; Wang, J.; Du, J.; Hou, X.; Ren, Y.; Han, Z. Stochastic Optimization-Aided Energy-Efficient Information Collection in Internet of Underwater Things Networks. *IEEE Internet Things J.* **2022**, *9*, 1775–1789. [CrossRef]
9. Alfouzan, F.A. Energy-efficient collision avoidance MAC protocols for underwater sensor networks: Survey and challenges. *J. Mar. Sci. Eng.* **2021**, *9*, 741. [CrossRef]
10. Luo, H.; Wang, J.; Bu, F.; Ruby, R.; Wu, K.; Guo, Z. Recent progress of air/water cross-boundary communications for underwater sensor networks: A review. *IEEE Sens. J.* **2022** , *22*, 8360–8382. [CrossRef]
11. Mozaffari, M.; Saad, W.; Bennis, M.; Nam, Y.H.; Debbah, M. A tutorial on UAVs for wireless networks: Applications, challenges, and open problems. *IEEE Commun. Surv. Tutor.* **2019**, *21*, 2334–2360. [CrossRef]
12. Hayat, S.; Yanmaz, E.; Muzaffar, R. Survey on Unmanned Aerial Vehicle Networks for Civil Applications: A Communications Viewpoint. *IEEE Commun. Surv. Tutor.* **2016**, *18*, 2624–2661. [CrossRef]
13. Wang, Y.; Su, Z.; Ni, J.; Zhang, N.; Shen, X. Blockchain-Empowered Space-Air-Ground Integrated Networks: Opportunities, Challenges, and Solutions. *IEEE Commun. Surv. Tutor.* **2022**, *24*, 160–209. [CrossRef]
14. Zhang, W.; Li, L.; Zhang, N.; Han, T.; Wang, S. Air-Ground Integrated Mobile Edge Networks: A Survey. *IEEE Access* **2020**, *8*, 125998–126018. [CrossRef]
15. Wei, T.; Feng, W.; Chen, Y.; Wang, C.X.; Ge, N.; Lu, J. Hybrid Satellite-Terrestrial Communication Networks for the Maritime Internet of Things: Key Technologies, Opportunities, and Challenges. *IEEE Internet Things J.* **2021**, *8*, 8910–8934. [CrossRef]
16. Su, N.; Wang, J.B.; Zeng, C.; Zhang, H.; Lin, M.; Li, G.Y. Unmanned Surface Vehicle Aided Maritime Data Collection Using Deep Reinforcement Learning. *IEEE Internet Things J.* **2022**, *9*, 19773–19786 . [CrossRef]
17. Zhang, Y.; Lyu, J.; Fu, L. Energy-Efficient Cyclical Trajectory Design for UAV-Aided Maritime Data Collection in Wind. In Proceedings of the GLOBECOM 2020–2020 IEEE Global Communications Conference, Taipei, Taiwan, 7–11 December 2020; pp. 1–6. [CrossRef]
18. Wang, H.; Wang, Y.; Ma, Y.; Lin, B. Resource Allocation for OFDM-based Maritime Edge Computing Networks. In Proceedings of the 2020 13th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Chengdu, China, 17–19 October 2020; pp. 983–988. [CrossRef]
19. Zeng, H.; Li, R.; Su, Z.; Xu, Q.; Wang, Y.; Dai, M.; Luan, T.H.; Sun, X.; Liu, D. Collaborative Computation Offloading for UAVs and USV Fleets in Communication Networks. In Proceedings of the 2022 International Wireless Communications and Mobile Computing (IWCMC), Dubrovnik, Croatia, 30 May–3 June 2022; pp. 949–954. [CrossRef]
20. Yang, T.; Feng, H.; Yang, C.; Wang, Y.; Dong, J.; Xia, M. Multivessel Computation Offloading in Maritime Mobile Edge Computing Network. *IEEE Internet Things J.* **2019**, *6*, 4063–4073. [CrossRef]

21. Dai, M.; Wu, Y.; Qian, L.; Su, Z.; Lin, B.; Chen, N. UAV-Assisted Multi-Access Computation Offloading Via Hybrid NOMA and FDMA in Marine Networks. *IEEE Trans. Netw. Sci. Eng.* **2022**, 1–15 . [CrossRef]
22. Wang, Z.; Su, X.; Xin, Y. Multi-access Edge Computing Offloading Method Oriented to Offshore Scenarios. In Proceedings of the 2021 IEEE/CIC International Conference on Communications in China (ICCC), Xiamen, China, 28–30 July 2021; pp. 1–6. [CrossRef]
23. Xiao, A.; Chen, H.; Wu, S.; Zhang, P.; Li, H.; Ma, L. Voyage-Based Computation Offloading for Secure Maritime Edge Networks. In Proceedings of the 2020 IEEE Globecom Workshops (GC Wkshps), Taipei, Taiwan, 7–11 December 2020; pp. 1–6. [CrossRef]
24. Liu, Y.; Yan, J.; Zhao, X. Deep Reinforcement Learning Based Latency Minimization for Mobile Edge Computing with Virtualization in Maritime UAV Communication Network. *IEEE Trans. Veh. Technol.* **2022**, *71*, 4225–4236. [CrossRef]
25. Dai, Y.; Lin, B.; Che, Y.; Lyu, L. UAV-assisted data offloading for smart container in offshore maritime communications. *China Commun.* **2022**, *19*, 153–165. [CrossRef]
26. Ma, R.; Wang, R.; Liu, G.; Meng, W.; Liu, X. UAV-aided cooperative data collection scheme for ocean monitoring networks. *IEEE Internet Things J.* **2021**, *8*, 13222–13236. [CrossRef]
27. Yang, T.; Feng, H.; Gao, S.; Jiang, Z.; Qin, M.; Cheng, N.; Bai, L. Two-stage offloading optimization for energy–latency tradeoff with mobile edge computing in maritime Internet of Things. *IEEE Internet Things J.* **2019**, *7*, 5954–5963. [CrossRef]
28. Wang, Z.; Lin, B.; Sun, L.; Wang, Y. Intelligent Task Offloading for 6G-Enabled Maritime IoT Based on Reinforcement Learning. In Proceedings of the 2021 International Conference on Security, Pattern Analysis, and Cybernetics (SPAC), Chengdu, China, 18–20 June 2021; pp. 566–570.
29. Xiao, A.; Wang, X.; Wu, S.; Jiang, C.; Ma, L. Mobility-Aware Resource Management for Integrated Satellite-Maritime Mobile Networks. *IEEE Netw.* **2022**, *36*, 121–127. [CrossRef]
30. Gao, S.; Yang, T.; Ni, H.; Zhang, G. Multi-Armed Bandits Scheme for Tasks Offloading in MEC-enabled Maritime Communication Networks. In Proceedings of the 2020 IEEE/CIC International Conference on Communications in China (ICCC), Chongqing, China, 9–11 August 2020; pp. 232–237. [CrossRef]
31. Xu, F.; Yang, F.; Zhao, C.; Wu, S. Deep reinforcement learning based joint edge resource management in maritime network. *China Commun.* **2020**, *17*, 211–222. [CrossRef]
32. Yang, T.; Chen, J.; Zhang, N. AI-Empowered Maritime Internet of Things: A Parallel-Network-Driven Approach. *IEEE Netw.* **2020**, *34*, 54–59. [CrossRef]
33. Liu, Q.; Liang, H.; Luo, R.; Liu, Q. Energy-Efficiency Computation Offloading Strategy in UAV Aided V2X Network with Integrated Sensing and Communication. *IEEE Open J. Commun. Soc.* **2022**, *3*, 1337–1346. [CrossRef]
34. Meng, K.; Wu, Q.; Ma, S.; Chen, W.; Quek, T.Q.S. UAV Trajectory and Beamforming Optimization for Integrated Periodic Sensing and Communication. *IEEE Wirel. Commun. Lett.* **2022**, *11*, 1211–1215. [CrossRef]
35. Lyu, Z.; Zhu, G.; Xu, J. Joint Trajectory and Beamforming Design for UAV-Enabled Integrated Sensing and Communication. In Proceedings of the ICC 2022—IEEE International Conference on Communications, Seoul, Korea, 16–20 May 2022; pp. 1593–1598. [CrossRef]
36. Zhang, K.; Shen, C. UAV Aided Integrated Sensing and Communications. In Proceedings of the 2021 IEEE 94th Vehicular Technology Conference (VTC2021-Fall), Norman, OK, USA, 27–30 September 2021; pp. 1–6. [CrossRef]
37. Huang, N.; Wang, T.; Wu, Y.; Wu, Q.; Quek, T.Q.S. Integrated Sensing and Communication Assisted Mobile Edge Computing: An Energy-Efficient Design via Intelligent Reflecting Surface. *IEEE Wirel. Commun. Lett.* **2022**, *11*, 2085–2089. [CrossRef]
38. Ding, C.; Wang, J.B.; Zhang, H.; Lin, M.; Li, G.Y. Joint MIMO Precoding and Computation Resource Allocation for Dual-Function Radar and Communication Systems with Mobile Edge Computing. *IEEE J. Sel. Areas Commun.* **2022**, *40*, 2085–2102. [CrossRef]
39. Jahanbakht, M.; Xiang, W.; Hanzo, L.; Azghadi, M.R. Internet of underwater things and big marine data analytics—a comprehensive survey. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 904–956. [CrossRef]
40. Liu, R.W.; Nie, J.; Garg, S.; Xiong, Z.; Zhang, Y.; Hossain, M.S. Data-driven trajectory quality improvement for promoting intelligent vessel traffic services in 6G-enabled maritime IoT systems. *IEEE Internet Things J.* **2020**, *8*, 5374–5385. [CrossRef]
41. Zhang, J.; Han, G.; Sha, J.; Qian, Y.; Liu, J. AUV-assisted subsea exploration method in 6G enabled deep ocean based on a cooperative pac-men mechanism. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 1649–1660. [CrossRef]
42. Liu, Y.; Wang, C.X.; Chang, H.; He, Y.; Bian, J. A novel non-stationary 6G UAV channel model for maritime communications. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 2992–3005. [CrossRef]
43. Wang, J.B.; Zeng, C.; Ding, C.; Zhang, H.; Lin, M.; Wang, J. Unmanned Surface Vessel Assisted Maritime Wireless Communication Toward 6G: Opportunities and Challenges. *IEEE Wirel. Commun.* **2022,** 1–17. [CrossRef]
44. Gong, S.; Lu, X.; Hoang, D.T.; Niyato, D.; Shu, L.; Kim, D.I.; Liang, Y.C. Toward Smart Wireless Communications via Intelligent Reflecting Surfaces: A Contemporary Survey. *IEEE Commun. Surv. Tutor.* **2020**, *22*, 2283–2314. [CrossRef]
45. Wu, Q.; Zhang, R. Beamforming Optimization for Wireless Network Aided by Intelligent Reflecting Surface with Discrete Phase Shifts. *IEEE Trans. Commun.* **2020**, *68*, 1838–1851. [CrossRef]
46. Dong, L.; Liu, Z.; Jiang, F.; Wang, K. Joint Optimization of Deployment and Trajectory in UAV and IRS-Assisted IoT Data Collection System. *IEEE Internet Things J.* **2022**, *9*, 21583–21593. [CrossRef]
47. Xu, J.; Kang, X.; Zhang, R.; Liang, Y.C. Joint Power and Trajectory Optimization for IRS-aided Master-Auxiliary-UAV-powered IoT Networks. In Proceedings of the 2021 IEEE Global Communications Conference (GLOBECOM), Madrid, Spain, 7–11 December 2021; pp. 1–6. [CrossRef]

48. Mahmoud, A.; Muhaidat, S.; Sofotasios, P.C.; Abualhaol, I.; Dobre, O.A.; Yanikomeroglu, H. Intelligent Reflecting Surfaces Assisted UAV Communications for IoT Networks: Performance Analysis. *IEEE Trans. Green Commun. Netw.* **2021**, *5*, 1029–1040. [CrossRef]
49. Solanki, S.; Gautam, S.; Sharma, S.K.; Chatzinotas, S. Ambient Backscatter Assisted Co-Existence in Aerial-IRS Wireless Networks. *IEEE Open J. Commun. Soc.* **2022**, *3*, 608–621. [CrossRef]
50. Liu, Y.; Han, F.; Zhao, S. Flexible and Reliable Multiuser SWIPT IoT Network Enhanced by UAV-Mounted Intelligent Reflecting Surface. *IEEE Trans. Reliab.* **2022**, *71*, 1092–1103. [CrossRef]
51. Li, Z.; Chen, W.; Cao, H.; Tang, H.; Wang, K.; Li, J. Joint Communication and Trajectory Design for Intelligent Reflecting Surface Empowered UAV SWIPT Networks. *IEEE Trans. Veh. Technol.* **2022**, 1–16. [CrossRef]
52. Mei, C.; Fang, Y.; Qiu, L. Dual Based Optimization Method for IRS-Aided UAV-Enabled SWIPT System. In Proceedings of the 2022 IEEE Wireless Communications and Networking Conference (WCNC), Austin, TX, USA, 10–13 April 2022; pp. 890–895. [CrossRef]
53. Yu, K.; Yu, X.; Cai, J. UAVs Assisted Intelligent Reflecting Surfaces SWIPT System with Statistical CSI. *IEEE J. Sel. Top. Signal Process.* **2021**, *15*, 1095–1109. [CrossRef]
54. Jiao, S.; Fang, F.; Zhou, X.; Zhang, H. Joint Beamforming and Phase Shift Design in Downlink UAV Networks with IRS-Assisted NOMA. *J. Commun. Inf. Netw.* **2020**, *5*, 138–149. [CrossRef]
55. Liu, C.H.; Syed, M.A.; Wei, L. Toward Ubiquitous and Flexible Coverage of UAV-IRS-Assisted NOMA Networks. In Proceedings of the 2022 IEEE Wireless Communications and Networking Conference (WCNC), Austin, TX, USA, 10–13 April 2022; pp. 1749–1754. [CrossRef]
56. Mu, X.; Liu, Y.; Guo, L.; Lin, J.; Poor, H.V. Intelligent Reflecting Surface Enhanced Multi-UAV NOMA Networks. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 3051–3066. [CrossRef]
57. Solanki, S.; Park, J.; Lee, I. On the Performance of IRS-Aided UAV Networks with NOMA. *IEEE Trans. Veh. Technol.* **2022**, *71*, 9038–9043. [CrossRef]
58. Cai, Y.; Wei, Z.; Hu, S.; Liu, C.; Ng, D.W.K.; Yuan, J. Resource Allocation and 3D Trajectory Design for Power-Efficient IRS-Assisted UAV-NOMA Communications. *IEEE Trans. Wirel. Commun.* **2022**, 1–1. [CrossRef]
59. Wang, Y.; Feng, W.; Wang, J.; Quek, T.Q. Hybrid satellite-UAV-terrestrial networks for 6G ubiquitous coverage: A maritime communications perspective. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 3475–3490. [CrossRef]
60. Shang, B.; Yi, Y.; Liu, L. Computing over Space-Air-Ground Integrated Networks: Challenges and Opportunities. *IEEE Netw.* **2021**, *35*, 302–309. [CrossRef]
61. Zeng, J.; Sun, J.; Wu, B.; Su, X. Mobile edge communications, computing, and caching (MEC3) technology in the maritime communication network. *China Commun.* **2020**, *17*, 223–234. [CrossRef]
62. Liu, Y.; Qin, Z.; Elkashlan, M.; Ding, Z.; Nallanathan, A.; Hanzo, L. Non-orthogonal multiple access for 5G and beyond. *Proc. IEEE* **2017**, *105*, 2347–2381. [CrossRef]
63. Guo, H.; Liu, J. Collaborative computation offloading for multiaccess edge computing over fiber–wireless networks. *IEEE Trans. Veh. Technol.* **2018**, *67*, 4514–4526. [CrossRef]
64. Wu, Y.; Ni, K.; Zhang, C.; Qian, L.P.; Tsang, D.H. NOMA-assisted multi-access mobile edge computing: A joint optimization of computation offloading and time allocation. *IEEE Trans. Veh. Technol.* **2018**, *67*, 12244–12258. [CrossRef]
65. Tang, R.; Feng, W.; Chen, Y.; Ge, N. NOMA-based UAV communications for maritime coverage enhancement. *China Commun.* **2021**, *18*, 230–243. [CrossRef]
66. Fang, X.; Feng, W.; Wang, Y.; Chen, Y.; Ge, N.; Ding, Z.; Zhu, H. NOMA-Based Hybrid Satellite-UAV-Terrestrial Networks for 6G Maritime Coverage. *IEEE Trans. Wirel. Commun.* **2022**. [CrossRef]
67. Hassan, S.S.; Tun, Y.K.; Saad, W.; Han, Z.; Hong, C.S. Blue Data Computation Maximization in 6G Space-Air-Sea Non-Terrestrial Networks. In Proceedings of the 2021 IEEE Global Communications Conference (GLOBECOM), Madrid, Spain, 7–11 December 2021; pp. 1–6. [CrossRef]
68. Zhu, C.; Zhang, W.; Chiang, Y.; Ye, N.; Du, L.; An, J. Software-Defined Maritime Fog Computing: Architecture, Advantages, and Feasibility. *IEEE Netw.* **2022**, *36*, 26–33. [CrossRef]
69. Ai, Q.; Qiao, X.; Liao, Y.; Yu, Q. Joint Optimization of USVs Communication and Computation Resource in IRS-Aided Wireless Inland Ship MEC Networks. *IEEE Trans. Green Commun. Netw.* **2022**, *6*, 1023–1036. [CrossRef]
70. Cheng, X.; Qu, F.; Yang, L. Single carrier FDMA over underwater acoustic channels. In Proceedings of the 2011 6th International ICST Conference on Communications and Networking in China (CHINACOM), Yokohama, Japan, 6–9 May 2012; IEEE, 2011; pp. 1052–1057.
71. Yu, W.; Chen, Y.; Wan, L.; Zhang, X.; Zhu, P.; Xu, X. An energy optimization clustering scheme for multi-hop underwater acoustic cooperative sensor networks. *IEEE Access* **2020**, *8*, 89171–89184. [CrossRef]
72. Demir, H.S.; Christen, J.B.; Ozev, S. Energy-efficient image recognition system for marine life. *IEEE Trans. Comput.-Aided Des. Integr. Circuits Syst.* **2020**, *39*, 3458–3466. [CrossRef]
73. Geng, X.; Wang, Y.; Feng, H.; Zhang, L. Lanepost: Lane-based optimal routing protocol for delay-tolerant maritime networks. *China Commun.* **2017**, *14*, 65–78. [CrossRef]
74. Zhou, X.; Li, Y.; He, D.; Zhang, C.; Ji, X. Energy-efficient channel allocation based data aggregation for intertidal wireless sensor networks. *IEEE Sens. J.* **2021**, *21*, 17386–17394. [CrossRef]

75. Lin, Z.; Chen, X.; Chen, P. Energy harvesting space-air-sea integrated networks for MEC-enabled maritime Internet of Things. *China Commun.* **2022**, *19*, 47–57. [CrossRef]
76. Liu, X.; Zhai, X.B.; Lu, W.; Wu, C. QoS-guarantee resource allocation for multibeam satellite industrial internet of things with NOMA. *IEEE Trans. Ind. Inform.* **2019**, *17*, 2052–2061. [CrossRef]
77. Zhang, J.; Dai, M.; Su, Z. Task allocation with unmanned surface vehicles in smart ocean IoT. *IEEE Internet Things J.* **2020**, *7*, 9702–9713. [CrossRef]
78. Ranaweera, P.; Jurcut, A.D.; Liyanage, M. Survey on Multi-Access Edge Computing Security and Privacy. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 1078–1124. [CrossRef]
79. Abbas, N.; Zhang, Y.; Taherkordi, A.; Skeie, T. Mobile Edge Computing: A Survey. *IEEE Internet Things J.* **2018**, *5*, 450–465. [CrossRef]
80. Cao, K.; Liu, Y.; Meng, G.; Sun, Q. An Overview on Edge Computing Research. *IEEE Access* **2020**, *8*, 85714–85728. [CrossRef]
81. Feng, C.; Yu, K.; Aloqaily, M.; Alazab, M.; Lv, Z.; Mumtaz, S. Attribute-Based Encryption with Parallel Outsourced Decryption for Edge Intelligent IoV. *IEEE Trans. Veh. Technol.* **2020**, *69*, 13784–13795. [CrossRef]
82. Liu, J.; Li, Y.; Sun, R.; Pei, Q.; Zhang, N.; Dong, M.; Leung, V.C.M. EMK-ABSE: Efficient Multi-Keyword Attribute-Based Searchable Encryption Scheme Through Cloud-Edge Coordination. *IEEE Internet Things J.* **2022**, *9*, 18650–18662. [CrossRef]
83. Wu, J.; Sheng, X.; Li, G.; Yu, K.; Liu, J. An efficient and secure aggregation encryption scheme in edge computing. *China Commun.* **2022**, *19*, 245–257. [CrossRef]
84. Hu, F.; Chen, B. Channel Coding Scheme for Relay Edge Computing Wireless Networks via Homomorphic Encryption and NOMA. *IEEE Trans. Cogn. Commun. Netw.* **2020**, *6*, 1180–1192. [CrossRef]
85. Jameel, F.; Wyne, S.; Kaddoum, G.; Duong, T.Q. A Comprehensive Survey on Cooperative Relaying and Jamming Strategies for Physical Layer Security. *IEEE Commun. Surv. Tutor.* **2019**, *21*, 2734–2771. [CrossRef]
86. Huo, Y.; Tian, Y.; Ma, L.; Cheng, X.; Jing, T. Jamming Strategies for Physical Layer Security. *IEEE Wirel. Commun.* **2018**, *25*, 148–153. [CrossRef]
87. Lim, W.Y.B.; Luong, N.C.; Hoang, D.T.; Jiao, Y.; Liang, Y.C.; Yang, Q.; Niyato, D.; Miao, C. Federated Learning in Mobile Edge Networks: A Comprehensive Survey. *IEEE Commun. Surv. Tutor.* **2020**, *22*, 2031–2063. [CrossRef]
88. Cui, G.; He, Q.; Li, B.; Xia, X.; Chen, F.; Jin, H.; Xiang, Y.; Yang, Y. Efficient Verification of Edge Data Integrity in Edge Computing Environment. *IEEE Trans. Serv. Comput.* **2021**, 1–1. [CrossRef]
89. Li, B.; He, Q.; Chen, F.; Jin, H.; Xiang, Y.; Yang, Y. Inspecting Edge Data Integrity with Aggregated Signature in Distributed Edge Computing Environment. *IEEE Trans. Cloud Comput.* **2021**, 1. [CrossRef]
90. Yu, H.; Hu, Q.; Yang, Z.; Liu, H. Efficient Continuous Big Data Integrity Checking for Decentralized Storage. *IEEE Trans. Netw. Sci. Eng.* **2021**, *8*, 1658–1673. [CrossRef]
91. Shen, W.; Qin, J.; Yu, J.; Hao, R.; Hu, J. Enabling Identity-Based Integrity Auditing and Data Sharing With Sensitive Information Hiding for Secure Cloud Storage. *IEEE Trans. Inf. Forensics Secur.* **2019**, *14*, 331–346. [CrossRef]
92. Tong, W.; Chen, W.; Jiang, B.; Xu, F.; Li, Q.; Zhong, S. Privacy-Preserving Data Integrity Verification for Secure Mobile Edge Storage. *IEEE Trans. Mob. Comput.* **2022**, 1–1. [CrossRef]
93. Zheng, Z.; Xie, S.; Dai, H.N.; Chen, X.; Wang, H. Blockchain challenges and opportunities: A survey. *Int. J. Web Grid Serv.* **2018**, *14*, 352–375. [CrossRef]
94. Dai, H.N.; Zheng, Z.; Zhang, Y. Blockchain for Internet of Things: A Survey. *IEEE Internet Things J.* **2019**, *6*, 8076–8094. [CrossRef]
95. Cao, X.; Zhang, H.; Peng, M. Collaborative multiple access and energy-efficient resource allocation in distributed maritime wireless networks. *China Commun.* **2022**, *19*, 137–153. [CrossRef]
96. Zhang, M.; Cai, W. Energy-efficient depth based probabilistic routing within 2-hop neighborhood for underwater sensor networks. *IEEE Sens. Lett.* **2020**, *4*, 1–4. [CrossRef]
97. Su, Y.; Fan, R.; Fu, X.; Jin, Z. DQELR: An Adaptive Deep Q-Network-Based Energy- and Latency-Aware Routing Protocol Design for Underwater Acoustic Sensor Networks. *IEEE Access* **2019**, *7*, 9091–9104. [CrossRef]
98. Wang, M.; Chen, Y.; Sun, X.; Xiao, F.; Xu, X. Node Energy Consumption Balanced Multi-Hop Transmission for Underwater Acoustic Sensor Networks Based on Clustering Algorithm. *IEEE Access* **2020**, *8*, 191231–191241. [CrossRef]
99. Xing, G.; Chen, Y.; He, L.; Su, W.; Hou, R.; Li, W.; Zhang, C.; Chen, X. Energy Consumption in Relay Underwater Acoustic Sensor Networks for NDN. *IEEE Access* **2019**, *7*, 42694–42702. [CrossRef]
100. Chen, Y.; Jin, X.; Xu, X. Energy-efficient mobile data collection adopting node cooperation in an underwater acoustic sensor network. *China Commun.* **2017**, *14*, 32–42. [CrossRef]
101. Jing, L.; He, C.; Huang, J.; Ding, Z. Energy Management and Power Allocation for Underwater Acoustic Sensor Network. *IEEE Sens. J.* **2017**, *17*, 6451–6462. [CrossRef]
102. Zhang, T.; Wen, H.; Tang, J.; Song, H.; Xie, F. Cooperative Jamming Secure Scheme for IWNs Random Mobile Users Aided by Edge Computing Intelligent Node Selection. *IEEE Trans. Ind. Inform.* **2021**, *17*, 4999–5009. [CrossRef]
103. Qian, L.; Wu, W.; Lu, W.; Wu, Y.; Lin, B.; Quek, T.Q.S. Secrecy-Based Energy-Efficient Mobile Edge Computing via Cooperative Non-Orthogonal Multiple Access Transmission. *IEEE Trans. Commun.* **2021**, *69*, 4659–4677. [CrossRef]
104. Li, B.; Wu, W.; Zhao, W.; Zhang, H. Security Enhancement with a Hybrid Cooperative NOMA Scheme for MEC System. *IEEE Trans. Veh. Technol.* **2021**, *70*, 2635–2648. [CrossRef]

105. Cui, M.; Zhang, H.; Huang, Y.; Xu, Z.; Zhao, Q. A Fountain-Coding Based Cooperative Jamming Strategy for Secure Service Migration in Edge Computing. *Wirel. Netw.* **2021**, 1–14. [CrossRef]
106. Nguyen, D.C.; Ding, M.; Pathirana, P.N.; Seneviratne, A.; Li, J.; Poor, H.V. Federated learning for internet of things: A comprehensive survey. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 1622–1658. [CrossRef]
107. Chen, M.; Yang, Z.; Saad, W.; Yin, C.; Poor, H.V.; Cui, S. A joint learning and communications framework for federated learning over wireless networks. *IEEE Trans. Wirel. Commun.* **2020**, *20*, 269–283. [CrossRef]
108. Wu, Y.; Song, Y.; Wang, T.; Qian, L.; Quek, T.Q. Non-Orthogonal Multiple Access Assisted Federated Learning via Wireless Power Transfer: A Cost-Efficient Approach. *IEEE Trans. Commun.* **2022**, *70*, 2853–2869. [CrossRef]
109. Bao, W.; Wu, C.; Guleng, S.; Zhang, J.; Yau, K.L.A.; Ji, Y. Edge computing-based joint client selection and networking scheme for federated learning in vehicular IoT. *China Commun.* **2021**, *18*, 39–52. [CrossRef]
110. Zhou, J.; Wu, N.; Wang, Y.; Gu, S.; Cao, Z.; Dong, X.; Choo, K.K.R. A Differentially Private Federated Learning Model against Poisoning Attacks in Edge Computing. *IEEE Trans. Dependable Secur. Comput.* **2022**, 1. [CrossRef]
111. Mills, J.; Hu, J.; Min, G. Multi-Task Federated Learning for Personalised Deep Neural Networks in Edge Computing. *IEEE Trans. Parallel Distrib. Syst.* **2022**, *33*, 630–641. [CrossRef]
112. He, C.; Liu, G.; Guo, S.; Yang, Y. Privacy-Preserving and Low-Latency Federated Learning in Edge Computing. *IEEE Internet Things J.* **2022**, *9*, 20149–20159. [CrossRef]
113. Zhang, C.; Liu, X.; Zheng, X.; Li, R.; Liu, H. FengHuoLun: A Federated Learning based Edge Computing Platform for Cyber-Physical Systems. In Proceedings of the 2020 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), Taipei, Taiwan, 7–11 December 2020; pp. 1–4. [CrossRef]
114. Ye, Y.; Li, S.; Liu, F.; Tang, Y.; Hu, W. EdgeFed: Optimized Federated Learning Based on Edge Computing. *IEEE Access* **2020**, *8*, 209191–209198. [CrossRef]
115. Ahmed, K.M.; Imteaj, A.; Amini, M.H. Federated Deep Learning for Heterogeneous Edge Computing. In Proceedings of the 2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA), Pasadena, CA, USA, 13–16 December 2021; pp. 1146–1152. [CrossRef]
116. Amannejad, Y. Building and Evaluating Federated Models for Edge Computing. In Proceedings of the 2020 16th International Conference on Network and Service Management (CNSM), Izmir, Turkey, 2–6 November 2020; pp. 1–5. [CrossRef]
117. Wang, Y.; Su, Z.; Zhang, N.; Benslimane, A. Learning in the Air: Secure Federated Learning for UAV-Assisted Crowdsensing. *IEEE Trans. Netw. Sci. Eng.* **2021**, *8*, 1055–1069. [CrossRef]
118. Liu, Y.; Nie, J.; Li, X.; Ahmed, S.H.; Lim, W.Y.B.; Miao, C. Federated Learning in the Sky: Aerial-Ground Air Quality Sensing Framework with UAV Swarms. *IEEE Internet Things J.* **2021**, *8*, 9827–9837. [CrossRef]
119. Yang, H.; Zhao, J.; Xiong, Z.; Lam, K.Y.; Sun, S.; Xiao, L. Privacy-Preserving Federated Learning for UAV-Enabled Networks: Learning-Based Joint Scheduling and Resource Management. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 3144–3159. [CrossRef]
120. Do, Q.V.; Pham, Q.V.; Hwang, W.J. Deep Reinforcement Learning for Energy-Efficient Federated Learning in UAV-Enabled Wireless Powered Networks. *IEEE Commun. Lett.* **2022**, *26*, 99–103. [CrossRef]
121. Dai, Z.; Zhang, Y.; Zhang, W.; Luo, X.; He, Z. A Multi-Agent Collaborative Environment Learning Method for UAV Deployment and Resource Allocation. *IEEE Trans. Signal Inf. Process. Netw.* **2022**, *8*, 120–130. [CrossRef]
122. Mowla, N.I.; Tran, N.H.; Doh, I.; Chae, K. Federated Learning-Based Cognitive Detection of Jamming Attack in Flying Ad-Hoc Network. *IEEE Access* **2020**, *8*, 4338–4350. [CrossRef]
123. Qin, Z.; Ye, J.; Meng, J.; Lu, B.; Wang, L. Privacy-Preserving Blockchain-Based Federated Learning for Marine Internet of Things. *IEEE Trans. Comput. Soc. Syst.* **2022**, *9*, 159–173. [CrossRef]
124. Han, C.; Yang, T. Privacy Protection Technology of Maritime Multi-agent Communication Based on Part-Federated Learning. In Proceedings of the 2021 IEEE/CIC International Conference on Communications in China (ICCC Workshops), Xiamen, China, 28–30 July 2021; pp. 266–271. [CrossRef]
125. Zhang, Z.; Guan, C.; Chen, H.; Yang, X.; Gong, W.; Yang, A. Adaptive Privacy-Preserving Federated Learning for Fault Diagnosis in Internet of Ships. *IEEE Internet Things J.* **2022**, *9*, 6844–6854. [CrossRef]
126. Hammedi, W.; Brik, B.; Senouci, S.M. Toward Optimal MEC-Based Collision Avoidance System for Cooperative Inland Vessels: A Federated Deep Learning Approach. *IEEE Trans. Intell. Transp. Syst.* **2022**, 1–13. [CrossRef]
127. Su, Y.; Li, J.; Li, Y.; Su, Z. Edge-enabled: A Scalable and Decentralized Data Aggregation Scheme for IoT. *IEEE Trans. Ind. Inform.* **2022**, 1–1. [CrossRef]
128. Yuan, L.; He, Q.; Chen, F.; Zhang, J.; Qi, L.; Xu, X.; Xiang, Y.; Yang, Y. CSEdge: Enabling Collaborative Edge Storage for Multi-Access Edge Computing Based on Blockchain. *IEEE Trans. Parallel Distrib. Syst.* **2022**, *33*, 1873–1887. [CrossRef]
129. He, Y.; Wang, Y.; Qiu, C.; Lin, Q.; Li, J.; Ming, Z. Blockchain-Based Edge Computing Resource Allocation in IoT: A Deep Reinforcement Learning Approach. *IEEE Internet Things J.* **2021**, *8*, 2226–2237. [CrossRef]
130. Ni, Q.; Linfeng, Z.; Zhu, X.; Ali, I. A Novel Design Method of High Throughput Blockchain for 6G Networks: Performance Analysis and Optimization Model. *IEEE Internet Things J.* **2022**, 1. [CrossRef]
131. Guo, S.; Dai, Y.; Guo, S.; Qiu, X.; Qi, F. Blockchain Meets Edge Computing: Stackelberg Game and Double Auction Based Task Offloading for Mobile Blockchain. *IEEE Trans. Veh. Technol.* **2020**, *69*, 5549–5561. [CrossRef]
132. Guo, S.; Hu, X.; Guo, S.; Qiu, X.; Qi, F. Blockchain Meets Edge Computing: A Distributed and Trusted Authentication System. *IEEE Trans. Ind. Inform.* **2020**, *16*, 1972–1983. [CrossRef]

133. Wu, H.; Wolter, K.; Jiao, P.; Deng, Y.; Zhao, Y.; Xu, M. EEDTO: An Energy-Efficient Dynamic Task Offloading Algorithm for Blockchain-Enabled IoT-Edge-Cloud Orchestrated Computing. *IEEE Internet Things J.* **2021**, *8*, 2163–2176. [CrossRef]
134. Sheng, H.; Wang, S.; Zhang, Y.; Yu, D.; Cheng, X.; Lyu, W.; Xiong, Z. Near-Online Tracking with Co-Occurrence Constraints in Blockchain-Based Edge Computing. *IEEE Internet Things J.* **2021**, *8*, 2193–2207. [CrossRef]
135. Hosseini-Fahraji, A.; Loghmannia, P.; Zeng, K.; Li, X.; Yu, S.; Sun, S.; Wang, D.; Yang, Y.; Manteghi, M.; Zuo, L. Energy Harvesting Long-Range Marine Communication. In Proceedings of the IEEE INFOCOM 2020—IEEE Conference on Computer Communications, Toronto, ON, Canada, 6–9 July 2020; pp. 2036–2045. [CrossRef]
136. Khan, A.; Khan, M.; Ahmed, S.; Iqbal, N.; Abd Rahman, M.A.; Abdul Karim, M.K.; Mustafa, M.S.; Yaakob, Y. EH-IRSP: Energy Harvesting Based Intelligent Relay Selection Protocol. *IEEE Access* **2021**, *9*, 64189–64199. [CrossRef]
137. Saeed, N.; Celik, A.; Al-Naffouri, T.Y.; Alouini, M.S. Localization of Energy Harvesting Empowered Underwater Optical Wireless Sensor Networks. *IEEE Trans. Wirel. Commun.* **2019**, *18*, 2652–2663. [CrossRef]
138. Wang, R.; Yadav, A.; Makled, E.A.; Dobre, O.A.; Zhao, R.; Varshney, P.K. Optimal Power Allocation for Full-Duplex Underwater Relay Networks with Energy Harvesting: A Reinforcement Learning Approach. *IEEE Wirel. Commun. Lett.* **2020**, *9*, 223–227. [CrossRef]
139. Saeed, N.; Celik, A.; Al-Naffouri, T.Y.; Alouini, M.S. Energy harvesting hybrid acoustic-optical underwater wireless sensor networks localization. *Sensors* **2017**, *18*, 51. [CrossRef]
140. Li, R.; Zhang, H.; Wang, L.; Liu, G. A contact-mode triboelectric nanogenerator for energy harvesting from marine pipe vibrations. *Sensors* **2021**, *21*, 1514. [CrossRef] [PubMed]
141. Yang, L.; Huang, J.; Feng, B.; Zhang, F.; Zhang, Y.; Li, X.; Jian, J.; Wang, Z.; Tong, X. Undersea Wireless Power and Data Transfer System with Shared Channel Powered by Marine Renewable Energy System. *IEEE J. Emerg. Sel. Top. Circuits Syst.* **2022**, *12*, 242–250. [CrossRef]
142. Shin, Y.; Woo, S.; Lee, C.; Jeong, J.; Kwak, G.; Ahn, S. Design of a Wireless Power Transfer System with Two Inputs with Large Voltage Differences for Missiles Mounted on Maritime Vessels. *IEEE Access* **2022**, *10*, 70825–70839. [CrossRef]
143. Zhang, K.; Zhang, X.; Zhu, Z.; Yan, Z.; Song, B.; Mi, C.C. A New Coil Structure to Reduce Eddy Current Loss of WPT Systems for Underwater Vehicles. *IEEE Trans. Veh. Technol.* **2019**, *68*, 245–253. [CrossRef]
144. Huang, A.; Huang, M.; Shao, Z.; Zhang, X.; Wu, D.; Cao, C. A Practical Marine Wireless Sensor Network Monitoring System Based on LoRa and MQTT. In Proceedings of the 2019 IEEE 2nd International Conference on Electronics Technology (ICET), Malang, Indonesia, 4–5 October 2019; pp. 330–334. [CrossRef]
145. Zong, K. Marine resource exploration streamer control model based on artificial neural network. *J. Coast. Res.* **2020**, *103*, 855–859. [CrossRef]
146. Wenzhi, Z.; Suyun, H.; Wei, L.; Tongshan, W.; Yongxin, L. Petroleum geological features and exploration prospect of deep marine carbonate rocks in China onshore: A further discussion. *Nat. Gas Ind. B* **2014**, *1*, 14–23. [CrossRef]
147. Liu, Z.; Ling, M.; Zhu, T.; Xu, D. Safety Analysis of Shrinkage Monitoring Equipment in Marine Resource Exploration. *J. Coast. Res.* **2020**, *105*, 242–245. [CrossRef]
148. Pan, L. Exploration and mining learning robot of autonomous marine resources based on adaptive neural network controller. *Pol. Marit. Res.* **2018**, *25*, 78–83. [CrossRef]
149. Lyu, L.; Dai, Y.; Cheng, N.; Zhu, S.; Guan, X.; Lin, B.; Shen, X. AoI-aware co-design of cooperative transmission and state estimation for marine IoT systems. *IEEE Internet Things J.* **2020**, *8*, 7889–7901. [CrossRef]
150. Zeng, C.; Wang, J.B.; Ding, C.; Zhang, H.; Lin, M.; Cheng, J. Joint optimization of trajectory and communication resource allocation for unmanned surface vehicle enabled maritime wireless networks. *IEEE Trans. Commun.* **2021**, *69*, 8100–8115. [CrossRef]
151. Arienzo, L. Green RF/FSO communications in cognitive relay-based space information networks for maritime surveillance. *IEEE Trans. Cogn. Commun. Netw.* **2019**, *5*, 1182–1193. [CrossRef]
152. Yang, T.; Gao, S.; Li, J.; Qin, M.; Sun, X.; Zhang, R.; Wang, M.; Li, X. Multi-Armed Bandits Learning for Task Offloading in Maritime Edge Intelligence Networks. *IEEE Trans. Veh. Technol.* **2022**, *71*, 4212–4224. [CrossRef]
153. Duan, R.; Wang, J.; Zhang, H.; Ren, Y.; Hanzo, L. Joint multicast beamforming and relay design for maritime communication systems. *IEEE Trans. Green Commun. Netw.* **2019**, *4*, 139–151. [CrossRef]
154. Alcaraz, C.; Lopez, J. Digital Twin: A Comprehensive Survey of Security Threats. *IEEE Commun. Surv. Tutor.* **2022**, *24*, 1475–1503. [CrossRef]
155. Wu, Y.; Zhang, K.; Zhang, Y. Digital Twin Networks: A Survey. *IEEE Internet Things J.* **2021**, *8*, 13789–13804. [CrossRef]
156. Dai, M.; Wang, T.; Li, Y.; Wu, Y.; Qian, L.; Su, Z. Digital Twin Envisioned Secure Air-Ground Integrated Networks: A Blockchain-Based Approach. *IEEE Internet Things Mag.* **2022**, *5*, 96–103. [CrossRef]
157. Fan, B.; Wu, Y.; He, Z.; Chen, Y.; Quek, T.Q.; Xu, C.Z. Digital Twin Empowered Mobile Edge Computing for Intelligent Vehicular Lane-Changing. *IEEE Netw.* **2021**, *35*, 194–201. [CrossRef]
158. Duong, T.Q.; Van Huynh, D.; Li, Y.; Garcia-Palacios, E.; Sun, K. Digital Twin-enabled 6G Aerial Edge Computing with Ultra-Reliable and Low-Latency Communications: (Invited Paper). In Proceedings of the 2022 1st International Conference on 6G Networking (6GNet), Paris, France, 6–8 July 2022; pp. 1–5. [CrossRef]
159. Lu, Y.; Huang, X.; Zhang, K.; Maharjan, S.; Zhang, Y. Communication-Efficient Federated Learning for Digital Twin Edge Networks in Industrial IoT. *IEEE Trans. Ind. Inform.* **2021**, *17*, 5709–5718. [CrossRef]

160. Liu, J.; Li, C.; Bai, J.; Luo, Y.; Lv, H.; Lv, Z. Security in IoT-Enabled Digital Twins of Maritime Transportation Systems. *IEEE Trans. Intell. Transp. Syst.* **2021**, 1–9. [CrossRef]
161. Wen, J.; Yang, J.; Li, Y.; He, J.; Li, Z.; Song, H. Behavior-Based Formation Control Digital Twin for Multi-AUG in Edge Computing. *IEEE Trans. Netw. Sci. Eng.* **2022**, 1–11. [CrossRef]
162. Sun, S.; Wang, H.; Zhang, H.; Li, M.; Xiang, M.; Luo, C.; Ren, P. Underwater Image Enhancement with Reinforcement Learning. *IEEE J. Ocean. Eng.* **2022**, 1–13. [CrossRef]
163. Wang, N.; Gao, Y.; Zhang, X. Data-Driven Performance-Prescribed Reinforcement Learning Control of an Unmanned Surface Vehicle. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**, *32*, 5456–5467. [CrossRef] [PubMed]
164. Cheng, X.; Li, G.; Han, P.; Skulstad, R.; Chen, S.; Zhang, H. Data-Driven Modeling for Transferable Sea State Estimation Between Marine Systems. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 2561–2571. [CrossRef]
165. Zurowietz, M.; Nattkemper, T.W. Unsupervised Knowledge Transfer for Object Detection in Marine Environmental Monitoring and Exploration. *IEEE Access* **2020**, *8*, 143558–143568. [CrossRef]
166. Guo, J.; Guan, J. Classification of Marine Plankton Based on Few-shot Learning. *Arab. J. Sci. Eng.* **2021**, *46*, 9253–9262. [CrossRef]
167. Zhang, P.; Bai, Y.; Wang, D.; Bai, B.; Li, Y. Few-Shot Classification of Aerial Scene Images via Meta-Learning. *Remote Sens.* **2021**, *13*, 108. [CrossRef]
168. Zeng, D.; Gu, L.; Guo, S.; Cheng, Z.; Yu, S. Joint optimization of task scheduling and image placement in fog computing supported software-defined embedded system. *IEEE Trans. Comput.* **2016**, *65*, 3702–3712. [CrossRef]
169. Su, X.; Meng, L.; Huang, J. Intelligent Maritime Networking with Edge Services and Computing Capability. *IEEE Trans. Veh. Technol.* **2020**, *69*, 13606–13620. [CrossRef]
170. Munusamy, A.; Adhikari, M.; Khan, M.A.; Menon, V.G.; Srirama, S.N.; Alex, L.T.; Khosravi, M.R. Edge-Centric Secure Service Provisioning in IoT-Enabled Maritime Transportation Systems. *IEEE Trans. Intell. Transp. Syst.* **2021**, 1–10. [CrossRef]
171. Wen, J.; Yang, J.; Wei, W.; Lv, Z. Intelligent Multi-AUG Ocean Data Collection Scheme in Maritime Wireless Communication Network. *IEEE Trans. Netw. Sci. Eng.* **2022**, *9*, 3067–3079. [CrossRef]
172. Xie, H.; Qin, Z.; Li, G.Y.; Juang, B.H. Deep learning enabled semantic communication systems. *IEEE Trans. Signal Process.* **2021**, *69*, 2663–2675. [CrossRef]
173. Shi, G.; Xiao, Y.; Li, Y.; Xie, X. From semantic communication to semantic-aware networking: Model, architecture, and open problems. *IEEE Commun. Mag.* **2021**, *59*, 44–50. [CrossRef]
174. Zhang, H.; Shao, S.; Tao, M.; Bi, X.; Letaief, K.B. Deep Learning-Enabled Semantic Communication Systems with Task-Unaware Transmitter and Dynamic Data. *arXiv* **2022**, arXiv:2205.00271.
175. Xie, H.; Qin, Z. A lite distributed semantic communication system for internet of things. *IEEE J. Sel. Areas Commun.* **2020**, *39*, 142–153. [CrossRef]