

# AI-Aided Integrated Terrestrial and Non-Terrestrial 6G Solutions for Sustainable Maritime Networking

Salwa Saafi, Olga Vikhrova, Gábor Fodor, Jiri Hosek, and Sergey Andreev

**Abstract**—The maritime industry is experiencing a technological revolution that affects shipbuilding, operation of both seagoing and inland vessels, cargo management, and working practices in harbors. This ongoing transformation is driven by the ambition to make the ecosystem more sustainable and cost-efficient. Digitalization and automation help achieve these goals by transforming shipping and cruising into a much more cost- and energy-efficient, and decarbonized industry segment. The key enablers in these processes are always-available connectivity and content delivery services, which can not only aid shipping companies in improving their operational efficiency and reducing carbon emissions but also contribute to enhanced crew welfare and passenger experience. Due to recent advancements in integrating high-capacity and ultra-reliable terrestrial and non-terrestrial networking technologies, ubiquitous maritime connectivity is becoming a reality. To cope with the increased complexity of managing these integrated systems, this article advocates the use of artificial intelligence and machine learning-based approaches to meet the service requirements and energy efficiency targets in various maritime communications scenarios.

## I. INTRODUCTION

The maritime industry anticipates a substantial increase in the number of operating vessels, new harbors, and routes worldwide in response to the trade facilitation initiatives supported by the World Trade Organization. These initiatives aim to speed up international trade and unlock inclusive economic development. As a fast-growing sector, this industry is also experiencing external pressures due to environmental concerns. Today’s greenhouse gas emissions from shipping are estimated as 2.6% of the total global emissions, which is the equivalent of emissions from a large country [1]. To cope with this escalation, environmental sustainability and digital inclusion practices become fundamental and have to be incorporated across all maritime operations.

For *sustainable industry*, the maritime sector needs to go through an extensive optimization and evolution toward fully autonomous, globally connected, and digitalized operations with zero-emissions [2]. The success of automation of the maritime industry relies heavily on *dynamic networking* and *artificial intelligence (AI)* technologies that foster the emerging applications, such as intelligent harbors, remote on-board maintenance, and autonomous docking. These require unprecedentedly high data rates, large-scale connectivity between a large number of dissimilar terminals, life-long learning and inference at the smart end-points, and seamless operation of terrestrial and non-terrestrial networks.

Recent findings showed that nearly 90% of data generated on-board never leaves the deck, which means that operators are missing out on valuable insights and analytics for improved logistics, cost of maintenance, and resource utilization [3].

Owing to recent advances in satellite technology, the number of connected vessels has doubled over the last 5 years, but only 75% of vessels have on-board Internet access today. Satellite-based backhauling remains extremely costly and inherently limited, thus presenting serious challenges for the widespread technology adoption to meet the growing needs of the maritime industry. However, existing maritime communication systems offer dedicated services opportunistically (e.g., in proximity to coastal infrastructure), rather than genuinely inter-connecting humans, vessels, and ports into a holistic ecosystem.

While attempting to integrate several non-terrestrial networks into a unified infrastructure to facilitate the demanding intelligent broadband services for maritime operations, cellular Fifth Generation (5G) systems become increasingly convoluted and energy consuming, which risks compromising the fundamental need for sustainability [4]. By contrast, Sixth Generation (6G) technologies are envisaged not only as those employing higher frequencies (e.g., millimeter-wave (mmWave) and Terahertz bands) to achieve extreme throughputs, but also as solutions capable of supporting AI-aided closed-loop automation. Such systems are expected to enable the ultimate potential of the zero-touch architecture proposed by the European Telecommunications Standards Institute (ETSI) for fully automated networks [5].

In this article, we first examine the most important of the emerging maritime use cases, which call for a careful design of a *6G maritime network (6G-MN)* that facilitates communication and computation applications. The key components of 6G-MNs are dynamic networking – where communication links are created and activated on-demand – and distributed intelligence, where learning and inference are employed at different levels of the system. In our supportive study, we demonstrate how machine learning (ML) can aid and outperform traditional model-based approaches for energy-efficient topology management and scheduling in dynamic maritime networks. We then identify communication- and learning-related challenges in future AI-aided 6G-MNs.

The rest of this article is organized as follows. We first introduce the rationale for building future maritime communication systems around cellular networks and discuss the essential maritime use cases. We then review the challenges of sustainable operation in 6G-MNs and highlight the key role of AI for network-wide optimization in terms of topology management and resource allocation. We also summarize the open issues related to the integration of AI-based solutions in 6G-MNs and offer concluding remarks and future perspectives on this work in the final section.

## II. CELLULAR-ENABLED MARITIME NETWORKS

### A. Existing Maritime Communication Systems

Targeting navigation safety and maritime environment protection, the International Maritime Organization (IMO) and the International Telecommunication Union (ITU) cooperatively launched the global maritime distress and safety system (GMDSS). The latter includes a set of terrestrial and satellite radio technologies employed for people and vessel rescue in distress. To further improve ship-to-ship and ship-to-shore navigation accuracy, the IMO introduced the automatic identification system (AIS), which complements marine radars with tracking information for vessel collision avoidance and better situational awareness [6].

Despite being an effective technology for navigation assistance and maritime emergency services, the AIS provides low data rate communications for the exchange of basic navigation parameters such as speed, position, and direction [4]. This limitation motivated the International Association of Marine Aids to Navigation and Lighthouse Authorities (IALA) to develop their own very high frequency data exchange system (VDES). Building upon AIS capabilities, VDES encompasses several communication subsystems aiming to provide higher data rates, enhance the operating ranges by the integration of satellite components, augment security mechanisms, and support new maritime use cases such as e-Navigation [4]. The concept was introduced by the IMO to harmonize maritime navigation systems in offshore and coastal regions [6].

Although regulatory bodies continue to improve the systems discussed above, the ongoing evolution toward a digitalized maritime industry poses new challenges to maritime communication system design. With the increasing number of vessels, growing level of ship autonomy, and widespread adoption of Internet of Things (IoT) technologies, novel connectivity solutions need to ensure cost-efficiency, scalability, and service availability [7]. Such communication systems for modern maritime operations have to support not only the existing e-Navigation and GMDSS services, but also the emerging broadband and low-latency applications discussed in the sequel.

### B. Emerging 6G-MN Use Cases

Based on the IMO and AIS specifications and our understanding of market trends, the emerging maritime use cases can be grouped into six categories as illustrated in Fig. 1. This figure also maps the use cases onto connectivity requirements in terms of 5G service classes, namely, enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC).

The navigation and fleet management applications facilitate the exchange of telematic information for enhanced situational awareness and maritime fleet management. They provide mission-critical services for vessels of different types (i.e., cargo, law-enforcement, research, commercial, and leisure) and shore-based traffic management organizations using high-speed broadband links.

Shipborne IoT aims to improve on-board operation and navigation by communicating vessel's speed, fuel consump-

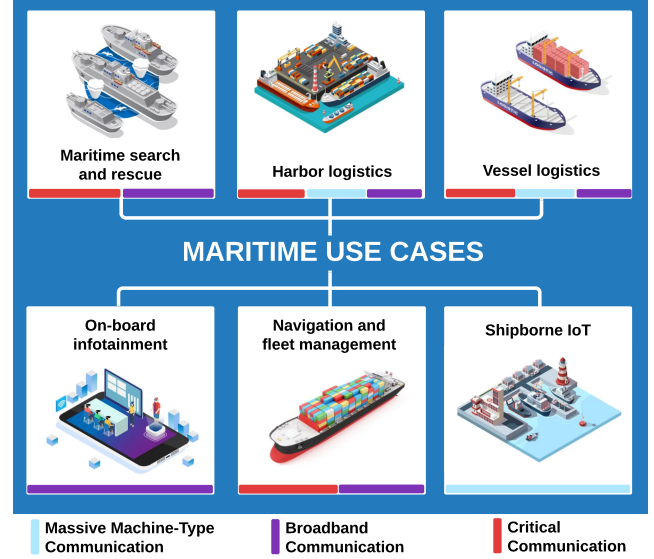


Fig. 1. Use case categories in 6G-MNs

tion, and carbon dioxide emission information to the on-board sensor fusion systems. Narrowband and massively deployed sensors generate abundant machine-type raw data for subsequent analysis and feature extraction. Vessel logistics is another shipborne use case category where the crew utilizes on-board communications for staff coordination and supply management and in the case of internal emergencies. On top of that, on-board infotainment provides passengers with access to video streaming, gaming, and interactive applications. These new shipborne use case categories comprise the requirements of broadband, critical, and massive machine-type communications, thus making the system highly heterogeneous in terms of traffic patterns, quality of service (QoS) requirements, and device capabilities.

As the name implies, the use case category of maritime search and rescue (SAR) provides medical emergency and “Man Overboard” rescue services that entail broadband and mission-critical applications to connect users in distress, on vessels, and around shore-based facilities. To continue with shore-based applications, harbor logistics offers a range of services for planning, organization, and inspection of harbors and industrial port operations. Ship loading/unloading coordination, asset tracking, warehouse management, short-sea, and feeder shipping can be monitored via these services. Similarly to vessel logistics use cases, harbor logistics may involve all three types of communication regimes.

### C. Prospective Solutions for 6G-MNs

Several attempts to interconnect vessels in coastal waters and build a bridge to the port have been successful by virtue of cellular coverage. However, due to the limited capacity of communication links, existing systems for maritime communications provided by, for example, Cellnex Telecom or Telenor Maritime, fail to cover deep offshore areas and support delay-critical and bandwidth-hungry use cases. By contrast, 5G and

TABLE I  
OVERVIEW OF ENABLING SOLUTIONS FOR MARITIME USE CASES

Solution	Related concepts	Relevant 6G-MN use cases
5G service classes	eMBB, URLLC, mMTC	Broadband, critical, and massive machine-type communications for all 6G-MN use cases
NR NTN	Satellite communication networks, unmanned aerial systems, HAPs	Coverage extension, network access in offshore areas and NLOS scenarios
Mobile IAB	Wireless backhaul, IAB-donor, IAB-nodes	Capacity improvement within a vessel, coverage extension in offshore areas
MCX services	MCPTT, MCData, MCVideo, off-network MCX	Rescue services, response to shipborne emergencies
LTE/NR sidelink	D2D communications, ProSe, UE-to-network relay	Ship-to-ship communications for navigation and collision avoidance, sensor group communications for shipborne IoT, relaying for coverage extension
MEC	Edge cloud servers, computation task offloading	Low latency and low energy consumption in shore-based and offshore applications
Cellular LPWA	LTE-M, NB-IoT, mMTC	Shipborne cellular IoT
NR RedCap	Industrial sensors, surveillance cameras, wearables	Using data collected by RedCap devices in several 6G-MN use cases
5G XR	AR, MR, VR	XR for mission-critical maritime SAR, XR conferencing for vessel logistics
5G LAN	5G LAN-type access, enterprise network communications	On-board services including vessel logistics and infotainment
NPN	Public network-integrated NPNs, standalone NPNs	Smart ports/harbors, enhanced on-board connectivity
Positioning	High-accuracy positioning, RAT-dependent, RAT-independent, hybrid solutions	Vessel location awareness for navigation and fleet management, indoor positioning services for staff management
Platooning	Cooperative platoons, autonomous vessels	Short-sea shipping and feeder services within harbor logistics use cases

beyond networks can provide a flexible and adaptive mobile communication platform for the modernization and long-term support of the maritime industry not only in coastal but also in offshore areas, as confirmed by the Third Generation Partnership Project (3GPP) in TR 22.819.

Initial 6G systems are to be primarily supported by the existing 5G infrastructures, thus benefiting from the advancement of cellular technologies that can foster the deployment of even more agile and intelligent applications discussed above. Enabling solutions, related cellular concepts, and relevant 6G-MN use cases are offered in Table I.

Hybrid satellite–terrestrial networks have been utilized to complement the high capacity of shore-based systems by the wide-area coverage of satellite communications. In addition to satellite access, New Radio (NR) technologies can support other non-terrestrial access components, such as high-altitude platforms (HAPs) as identified by 3GPP in TR 38.811. By employing solutions for NR to support non-terrestrial network (NTN), 6G-MNs can benefit from the 5-layer architecture for 6G setups as proposed in [8] to extend the coverage of terrestrial systems and provide access to maritime services in offshore areas and non-line-of-sight (NLOS) scenarios.

In addition to NR NTN, an attractive technology for coverage and capacity extension in terrestrial 5G and beyond networks is integrated access and backhaul (IAB), which was introduced by 3GPP TR 38.874 in Release 16. It is based on using part of the wireless access spectrum for the backhaul connections between remote base stations. While fixed IAB-nodes can extend the capacity of coastal 6G-MNs, mobile IAB, as suggested among the 3GPP Release 17 enhancements, can be employed for dynamic backhaul solutions, thus shaping mobile maritime mesh networks for both coverage and capacity extension. This can be considered as a more flexible, scalable, and affordable broadband access option for a wide range of cloud services.

Further, 3GPP public safety services, including mission-

critical push-to-talk (MCPTT), mission-critical data (MC-Data), and mission-critical video (MCVideo), can be applied for emergency services. These services can also be provided using the off-network mode in areas wherein cellular coverage is temporarily unavailable or network performance is limited in terms of capacity or latency.

NR sidelink for device-to-device (D2D) communications and proximity services (ProSe) can help avoid collisions as part of the navigation and fleet management use case. Sidelink-based ship-to-ship communications allow vessels to assist maritime coordination centers during SAR missions. User equipment (UE)-to-network relay, as another form of D2D wherein an indirect network connection is provided by a relay UE, can extend the coverage of terrestrial systems for shipborne applications in coastal waters.

In 5G networks, computation resources are moved closer to the end devices. Heavy computation tasks and raw data can be offloaded to proximate multi-access edge computing (MEC) servers, thus minimizing end-to-end transmission delays and energy consumption. Cellular low-power wide-area (LPWA) technologies, namely, LTE machine-type communications (LTE-M) and narrowband IoT (NB-IoT), can be deployed in 6G-MNs to support the use cases with mMTC requirements. In a similar context, the need for NR devices with reduced capabilities (RedCap), such as on-board industrial sensors, video surveillance cameras, and wearables, has been addressed by 3GPP in TR 38.875. Future 6G-MNs can benefit from the NR RedCap-enabled services for enhanced vessel navigation and monitoring, harbor logistics, and remote on-board assistance. The latter example refers to one of the extended reality (XR) use cases defined in TR 26.928, which includes augmented reality-guided assistance in remote locations, mixed reality-based sharing, and virtual reality-based telepresence collaboration.

Non-public network (NPN) and local area network (LAN)-type access for industrial IoT use cases has already been

considered by 3GPP for maritime scenarios in TR 22.819. With the planned enhancements in Release 17, NPNs can be employed in smart harbors to build private networks with adequate QoS and security guarantees. A range of positioning schemes, including radio access technology (RAT)-dependent and RAT-independent solutions, are ratified in 3GPP Release 16 specifications and can be used separately or in a hybrid manner to meet the required positioning accuracy in 6G-MN use cases. Accurate positioning can also enable future maritime platooning services. Aiming to improve navigation safety and reduce fuel consumption, autonomous vessels can move in cooperative platoons and be employed in feeder services to manage short-sea shipping from hub ports to feeder ports in inland waterways [9].

Recently, recognizing the high interest from maritime stakeholders, 3GPP has officially included the work on maritime communication (MARCOM) services over cellular systems in its beyond Release 16 standardization efforts in TS 22.119. An important challenge that needs to be considered in these systems is energy efficiency as part of the sustainability goal in maritime operations. Even though 5G NR system design offers better bit-per-Joule energy efficiency as compared to the previous generations of mobile technology, a typical 5G site has nearly 70% higher energy consumption than a base station deploying a mix of 2G, 3G, and 4G radios due to the use of additional power-hungry components [10]. Further cell densification together with link heterogeneity can make it difficult to optimize 5G and beyond deployments in real time, which calls for a more adaptive and less energy consuming system design discussed in the following section.

### III. AI FOR SUSTAINABLE MARITIME NETWORKING

#### A. Network Sustainability Challenges

The use cases identified in Fig. 1 are different from the scenarios behind the operation of well-established mobile and vehicular ad-hoc networks. For instance, they can create more stable multi-hop network formations over longer time spans, may need to transmit heterogeneous data over larger communication ranges, and might also include more complex and advanced on-board and in-port communication scenarios similar to industrial IoT applications.

A large volume of data generated on-board the vessels in deep offshore areas needs to be offloaded to the mainland for efficient port operation, or distributed further within the network to facilitate optimal maritime navigation and logistics. Real-time data collected along the navigation routes are crucial for autonomous shipping, as ports and vessels can access this information upon request. This can mitigate deviations from the optimal port operation and failures of communication links. In contrast, infotainment and extended reality-based applications for passengers and crew members of small vessels and large cruisers can require rapid dissemination of heavy content from the land to numerous destinations in different parts of the world. As these examples suggest, maritime operation targets robust, scalable, high-performance, and adaptive mechanisms for the orchestration of dissimilar services over dynamically formed mobile networks.

In 6G-MNs, multi-hop communications and flexible mesh topologies can be supported by IAB and D2D solutions. These technologies help overcome the vulnerabilities of highly directional and fast fading links, tolerate increased interference levels, and utilize radio resources more efficiently. However, due to node mobility within the unique and challenging integrated maritime infrastructure, 6G-MNs need to continuously adapt their resource allocation and scheduling policies over dynamic topologies.

Our envisaged 6G-MN illustrated in Fig. 2 comprises a high-performance terrestrial network segment that inherently supports operation and maintenance of smart harbors and industrial ports. The non-terrestrial part encompasses a dynamic IAB infrastructure, which ensures connectivity bridges between vessels and the terrestrial segment. The former facilitates inland shipping and ubiquitous monitoring of near-shore areas for improved human and marine life safety. An important component of this system is the powerful edge and cloud infrastructure for centralized and distributed learning to enable proactive and resource-wise on-demand operation.

Traditional model-based approaches and optimization algorithms may not be sufficient for satisfying the requirements of the above system. They typically struggle with a lack of timely global information about the system (e.g., channel and buffer states, user mobility, or demand level) to provide optimal control instructions and can thus yield impractical computations due to excessive model dimensions. In turn, data-driven methods are known to efficiently deal with both model and algorithm deficits, and with learning functional relations between different system parameters that are difficult to model. These parameters include (i) user profile data such as device position, mobility, transmission, and energy consumption patterns, (ii) network configuration data encompassing instantaneous link capacity and resource utilization, and node capabilities, and (iii) service data covering quality of experience, subscription to cooperative learning of a ML model, and capabilities for execution of offloaded tasks.

Allowing to extract valuable information from these massive data, AI techniques can be used to predict traffic peaks and system demands, detect anomalies or near-overload conditions, and identify nodes or clusters with high energy and resource consumption. This knowledge can alleviate the topology management and scheduling problems and underpin the solution design for self-optimized and automated 6G-MNs with energy-oriented optimization goals. In what follows, we provide examples of AI applications for a more energy-efficient maritime system operation.

#### B. Energy-Centric Topology Management

Since both system topology and network load may evolve over time, storage, compute, and spectrum resource allocations have to be provided on-demand and thus periodically re-optimized. To manage on-demand topologies, joint link activation and resource allocation problems need to be solved repeatedly, and potentially compared with previous configurations. As traditional model-based methods can be resource and time consuming, a more agile approach is required to facilitate the repetitive optimization problems.

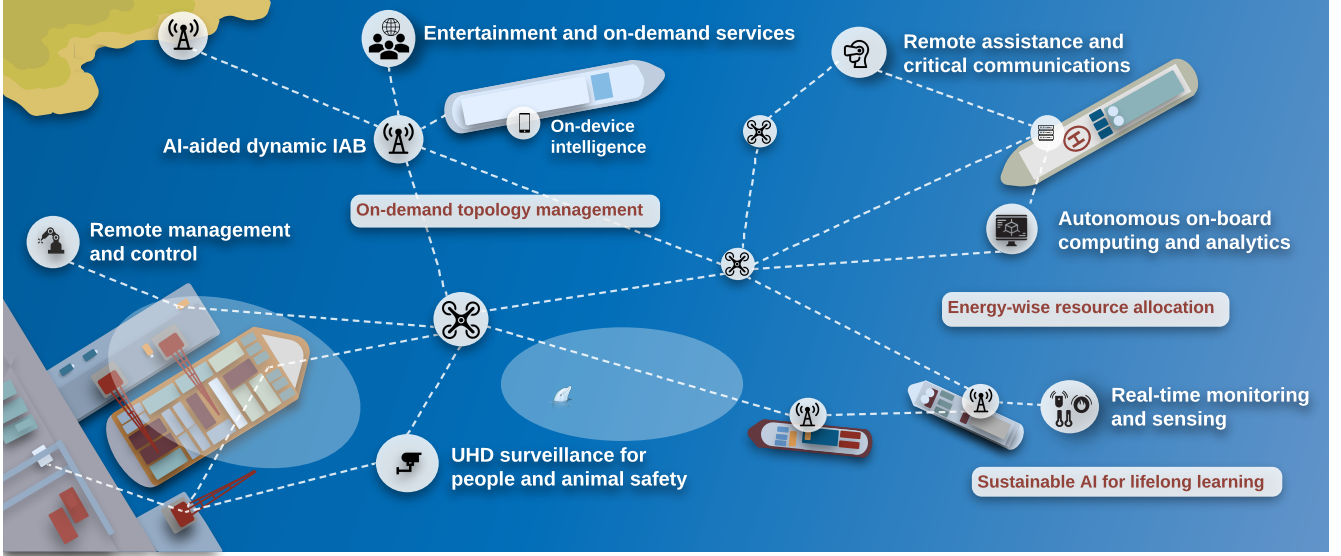


Fig. 2. Our vision of a unified, scalable, reliable, and intelligent 6G system with integrated features for sustainable maritime operations

As an illustrative example, we consider a low-dynamic multi-hop wireless network deployed over  $100 \text{ km}^2$ , where access nodes are uniformly distributed across the given area with the density of  $0.5 \text{ nodes per km}^2$ . Our goal is to minimize the network energy consumption while delivering heterogeneous traffic originating from cruisers or cargo vessels and rerouted to different destinations (e.g., harbors or other vessels). Therefore, we are aiming at the optimal allocation of time, spectrum, and power along the optimal routing paths.

Given that the scale of the above optimization problem increases with the number of nodes and potential routes, the performance of traditional optimization approaches can degrade dramatically. For solving the joint power allocation and link scheduling problem in this system to minimize its overall energy consumption, one needs to know all the possible allocation patterns to employ linear programming (LP). The number of patterns primarily depends on the number of potential links, though not all of them may eventually be used in the optimal solution [11].

Since the relation between the network flows and the set of active links in the optimal configuration cannot be obtained analytically, it may be learned by a data-driven method using information about only some of the optimal configurations (e.g., by solving optimization problem analytically for a number of system setups with fewer flows). Once the model is trained, it can efficiently predict which links are critical for the optimal configuration under any new traffic flows in the system. Therefore, by using a deep neural network (DNN), particularly its sub-category deep belief network (DBN), we reduce the number of links involved in the routing and scheduling decision in a given multi-hop layout, and thereby alleviate the complexity and execution time of finding the optimal configuration.

Hence, Fig. 3 demonstrates our system-level simulation results for the energy efficiency of a maritime communication

system operating at  $3.5 \text{ GHz}$  with different traffic loads defined as the maximum system capacity share. These results have been first obtained by using the DNN-aided LP optimization framework described in [11], and then compared to the baseline system operation.

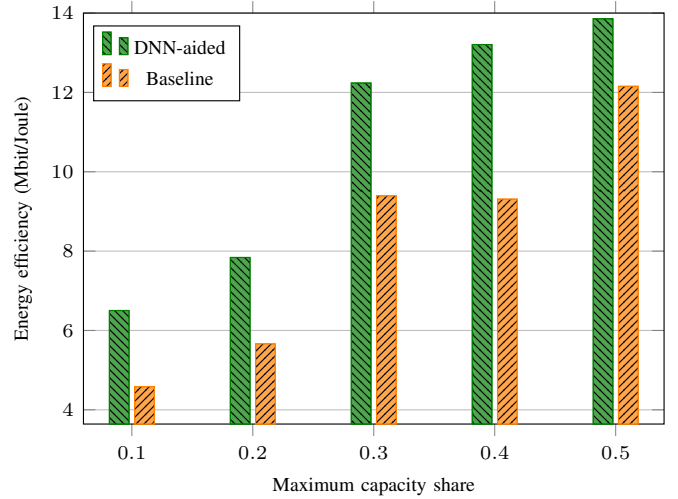


Fig. 3. Energy-efficient resource management for IAB-aided backhaul solution

Along these lines, other promising techniques such as long short-term memory (LSTM) and auto-encoder can be applied to discover the temporal and spatial correlations in traffic and support the formulation of multi-objective optimization problems. For critical services with ultra-low latency requirements, the challenge of routing is central. As shown in [12], a supervised DNN-aided traffic routing scheme causes much lower overheads than the traditional options such as open shortest path first (OSPF), while guaranteeing acceptable delay.

### C. Energy-Efficient Scheduling

Due to large- and small-scale node mobility, as well as interference fluctuations, the reported channel quality may become outdated, misleading, or even lost at the network side. Systematic inaccurate or imperfect knowledge of the channel state may cause significant QoS and energy efficiency degradation. Hence, mechanisms for channel quality prediction can help combat different types of link blockage effects and control radio interference while supporting redundant on-demand topologies.

Deep learning (DL) methods can improve the accuracy of channel reporting and, consequently, avoid inefficient resource utilization in the core network and radio access parts. They are well-suited for capturing non-linear and dynamic relationships between the model input and output data. They also have powerful prediction, inference, and data analysis capabilities owing to the large amounts of data generated by the environment and by the users. In particular, LSTM can handle time series problems, which makes them attractive for channel quality prediction and capable of alleviating the physical layer imperfections [13].

The results of our system-level simulations summarized in Fig. 4 demonstrate a significant improvement in energy efficiency by applying LSTM for resource scheduling. We employ an open-source interface between network simulator-3 and Python-based AI frameworks. The latter train the LSTM model using data generated by the simulator and then return the data from the trained model back to the simulator for testing. Communications over mmWave channels in a single-cell network topology with mobile UEs ( $10m/s$ ) are assumed. Unlike in the baseline scenario (i.e., without ML), in the LSTM-aided case the base station utilizes the predicted channel quality information when making decisions about scheduling and radio resource allocation [13]. Not only the system energy efficiency can be improved with better channel quality predictions, but also the end-to-end packet delay may be significantly decreased.

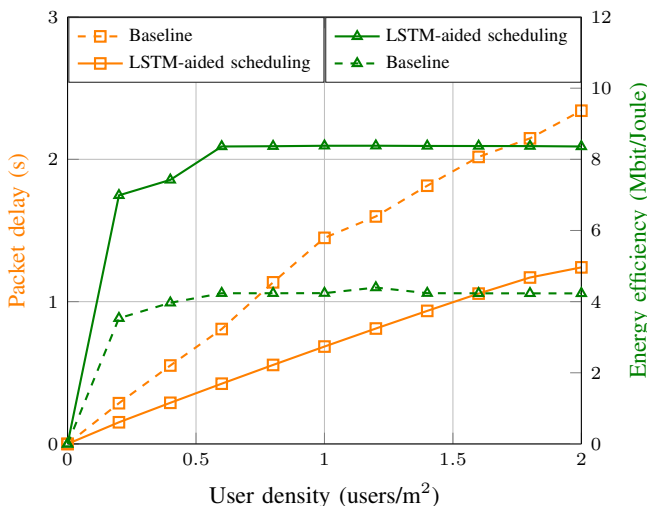


Fig. 4. Use of LSTM for energy-efficient real-time scheduling

## IV. OPEN ISSUES IN EMPLOYING AI FOR 6G-MNS

### A. From Centralized to Distributed Learning

As the adoption of AI technologies accelerates, the integration of various monitoring and control systems within a centralized cloud can limit the scalability in such systems. Hence, today's predominantly cloud-centric AI solutions that rely on training and inference in the remote cloud have to be complemented by more energy-efficient, partially distributed, and ultimately fully distributed learning mechanisms where numerous devices collaboratively train a part of a global model [14].

Pervasive system intelligence is vital for the evolution of maritime industry and its sustainable operation. In particular, real-time decision-making vastly improves port logistics and services. Through AI-assisted remote control, an operator can digitally escort vessels safely to port. Smart fleet and asset tracking features can improve load distribution in ports, which decreases the volumes of carbon dioxide near the port areas. XR applications for field engineers allow hands-on guidance from offsite support teams who can follow the operator's on-site view. All of these require lifelong learning where autonomous edge nodes (on-board the vessels or in dock areas) can participate in sensor data collection, processing, and sharing of resources for ML model training.

Conventionally, DNN algorithms are executed in the cloud where training data are preprocessed at the edge before being transferred to the cloud [14]. The edge/fog computing infrastructures are intended to accommodate the needs of multiple DNN models that require locality and persistent training. They also prevent the transmission of massive raw data over the network. Federated learning is a practical training mechanism wherein clients perform local ML training and forward their results to an aggregator for further inference. Devices, edge nodes, and cloud servers can be equivalently deemed as clients. Under the risk of involving clients with poor channel conditions or limited energy supply, ML model and client selection remains challenging in these distributed learning-based systems.

### B. UE Capabilities in Device-Level Solutions

Mobile RedCap devices such as wearables can assume a central role in real-time monitoring and ubiquitous sensing of critical and highly dynamic processes in maritime environments. Unmanned aerial vehicles help create situational awareness for hinterland and smart fairway scenarios as well as provide remote technical support for container handling equipment. Enhanced with additional on-device learning and inference capabilities, these systems can utilize real-time data to offer deeper insights into energy-efficient maritime operations. Beam misalignment in dynamic maritime environments may lead to significant data rate and energy efficiency degradation. DL-based proactive beam management at the device side can help avoid this potential limitation. Whenever the line-of-sight link is not available, reinforcement learning allows the identification of optimal relay nodes in online fashion, even with limited prior knowledge of the environment. However, selecting the optimal relay nodes is non-trivial in dynamic

environments and when both in-band and out-of-band relaying options are available.

In systems relying on device-level solutions, UE capabilities are crucial when selecting suitable ML models. For instance, if a moving IAB node is deployed on a floating platform or on-board a vessel, it can be connected to a source of renewable energy, while drones and wearable devices operate on battery. Therefore, not all devices in 6G-MNs are capable of training complex DNN due to their limited storage, processing, or power capacity. Standalone compression techniques (such as pruning) have been optimized only for DNN accuracy and without considering device energy consumption. By combining multiple compression techniques, one may derive compressed DL models with desired trade-offs between performance and resource utilization [15]. For instance, AdaDeep can automatically select various compression techniques to form a model according to not only device capability constraints but also application-driven requirements.

### C. Learning Delay and Network Reaction Time

In distributed learning under model or data split architecture, the involved nodes need to periodically communicate ML model parameters over the network. The time to synchronize their results can grow significantly due to in-network transfer delays. This synchronization latency can become even higher when using ML models such as DNNs with thousands of parameters. Although several solutions were proposed to reduce the DNN training times, the latter still depends on the used data samples and approximation functions. By properly selecting the nodes (e.g., depending on channel conditions and energy availability) and adjusting the ML model parameters (e.g., learning rates and number of epochs in DNNs), one can reduce the learning delay.

Learning delay and ML convergence criteria are central in future AI-aided 6G-MNs. In learning-aided architectures, network reaction time can become a new key performance indicator that tells how soon a new system configuration can be enabled. It may be defined as the time between a parameter change (e.g., number of active users or link quality) and the network response time including ML (re-)training and inference. Due to the limited communication ranges of high frequency radios, a potentially large number of hops may be required to connect two nodes of interest, which may cause an increase in the network reaction time under topology changes.

## V. CONCLUSIONS AND OUTLOOK

The convergence of AI and 6G allows to build sustainable AI-aided networks for maritime communications. With the envisaged 6G-MN, the maritime industry can benefit from the enabling effects of digitalization and virtualization in reducing carbon dioxide emissions in ports and vessels. 6G-MNs permit the integration of terrestrial and non-terrestrial network segments, applications, and services in a holistic manner to accommodate the need for large-scale, sustainable, and on-demand system infrastructures. Due to network complexity and dynamics, AI-aided solutions are indispensable for prompt and customized reactions of the network to demand

fluctuations. In particular, deep learning techniques discussed in this article can tackle 6G-MN optimization challenges at different levels.

The challenges of efficient learning over 6G-MNs are shaped by the distinctive features of the rapidly changing maritime environment, remote operation with limited availability of energy and communication resources, and considerable learning delays in distributed systems. However, several approaches discussed in this work, such as reinforcement learning, can be further developed and employed to address these issues. The insights offered by this article motivate further research that can address the open questions and challenges in intelligent 6G-MNs.

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## BIOGRAPHIES

SALWA SAAFI (saafi@vut.cz) is a Ph.D. student at the Department of Telecommunications at Brno University of Technology, Czech Republic and the Unit of Electrical Engineering at Tampere University, Finland. She received her engineering degree (2017) in telecommunications from the Higher School of Communication of Tunis, Tunisia. Her research interests include cellular radio access technologies, future wireless architectures, and wearable applications.

OLGA VIKHROVA (olga.vikhrova@tuni.fi) is a researcher at Tampere University, Finland. She received her Ph.D. (2021) in Information Engineering from University Mediterranea of Reggio Calabria, Italy, and M.Sc. (2014) in Information and Computer Science from Peoples' Friendship University of Russia (RUDN University), Russia. Her current research interests include distributed edge learning and computing, integrated access and backhaul networks, convergence of terrestrial and non-terrestrial networks.

GABOR FODOR (gaborf@kth.se) received his Ph.D. degree in electrical engineering from the Budapest University of Technology and Economics in 1998, his Docent degree from KTH Royal Institute of Technology, Stockholm, Sweden, in 2019, and his D.Sc. degree from the Hungarian Academy of Sciences in 2019. He is currently a master researcher with Ericsson Research and an adjunct professor with KTH Royal Institute of Technology. He was a co-recipient of the IEEE Communications Society Stephen O. Rice Prize in 2018. He is serving as the Chair of the IEEE Communications Society Full Duplex Emerging Technologies Initiative and as an Editor for IEEE Transactions on Wireless Communications and IEEE Wireless Communications.

JIRI HOSEK (hosek@vut.cz) received his M.S. and Ph.D. degrees in electrical engineering from the Faculty of Electrical Engineering and Communication at Brno University of Technology (BUT), Czech Republic, in 2007 and 2011, respectively. He is currently an Associate Professor (2016) and Deputy Vice-Head for R&D and International Relations at the Department of Telecommunications (2018), BUT. Jiri is also coordinating the WISLAB research group (2012), where he deals mostly with industry-oriented projects in the area of IoT and home automation services. Jiri (co-)authored more than 130 research works on networking technologies, wireless communications, quality of service, quality of experience, and IoT applications.

SERGEY ANDREEV (sergey.andreev@tuni.fi) is an associate professor of communications engineering and Academy Research Fellow at Tampere University, Finland. He has been a Visiting Senior Research Fellow with King's College London, UK (2018-20) and a Visiting Postdoc with University of California, Los Angeles, US (2016-17). He received his Ph.D. (2012) from TUT as well as his Specialist (2006), Cand.Sc. (2009), and Dr.Habil. (2019) degrees from SUAI. He served as lead series editor of the IoT Series (2018-21) for IEEE Communications Magazine and as editor for IEEE Wireless Communications Letters (2017-19).