

A Digital Twin-Based Intelligent Network Architecture for Underwater Acoustic Sensor Networks

Shanshan Song¹, Member, IEEE, Bingwen Huangfu, Jiani Guo², Jun Liu³, Member, IEEE, Junhong Cui, and Xuemin Shen⁴, Fellow, IEEE

I. INTRODUCTION

Abstract—Underwater acoustic sensor networks (UASNs) drive toward strong environmental adaptability, intelligence, and multifunctionality. However, due to unique UASN characteristics, such as long propagation delay, dynamic channel quality, and high attenuation, existing studies present untimeliness, inefficiency, and inflexibility in real practice. Digital twin (DT) technology is promising for UASNs to break the above bottlenecks by providing high-fidelity status prediction and exploring optimal schemes. In this article, we propose a Digital Twin-based Network Architecture (DTNA), enhancing UASNs' environmental adaptability, intelligence, and multifunctionality. By extracting real UASN information from local (node) and global (network) levels, we first design a layered architecture to improve the DT replica fidelity and UASN control flexibility. In local DT, we develop a resource allocation paradigm (RAPD), which rapidly perceives performance variations and iteratively optimizes allocation schemes to improve real-time environmental adaptability of resource allocation algorithms. In global DT, we aggregate decentralized local DT data and propose a collaborative Multi-agent reinforcement learning framework (CMFD) and a task-oriented network slicing (TNSD). CMFD patches scarce real data and provides extensive DT data to accelerate AI model training. TNSD unifies heterogeneous tasks' demand extraction and efficiently provides comprehensive network status, improving the flexibility of multi-task scheduling algorithms. Finally, practical and simulation experiments verify the high fidelity of DT. Compared with the original UASN architecture, experiment results demonstrate that DTNA can: (i) improve the timeliness and robustness of resource allocation; (ii) greatly reduce the training time of AI algorithms; (iii) more rapidly obtain network status for multi-task scheduling at a low cost.

Index Terms—Underwater acoustic sensor networks, digital twin, network architecture.

Received 5 September 2024; revised 24 January 2025; accepted 25 March 2025. Date of publication 28 March 2025; date of current version 6 August 2025. This work was supported by the National Natural Science Foundation of China under Grant 62101211 and Grant 62471201. Recommended for acceptance by H. Yao. (Corresponding author: Jiani Guo.)

Shanshan Song, Bingwen Huangfu, and Jiani Guo are with the College of Computer Science and Technology, Jilin University, Changchun 130012, China (e-mail: songss@jlu.edu.cn; hfbw24@mails.jlu.edu.cn; jn-guo20@mails.jlu.edu.cn).

Jun Liu is with the School of Electronic and Information Engineering, Beihang University, Beijing 100191, China (e-mail: liujun2019@buaa.edu.cn).

Junhong Cui is with the Shenzhen Institute for Advanced Study, University of Electronic Science and Technology of China, Shenzhen 518110, China, and also with the College of Computer Science and Technology, Jilin University, Changchun 130012, China (e-mail: junhong_cui@jlu.edu.cn).

Xuemin Shen is with the Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, ON N2L 3G1, Canada (e-mail: sshen@uwaterloo.ca).

Digital Object Identifier 10.1109/TMC.2025.3555640

UNDERWATER Acoustic Sensor Networks (UASNs) have been extensively utilized in various scenarios, such as auxiliary navigation, disaster warning, and autonomous exploration [1], [2], [3], [4], [5]. Given the evolving research on underwater applications, there is a desire for UASNs to possess strong environmental adaptability, intelligence, and multifunctionality. To achieve the above objectives, most existing studies are focused on resource allocation, AI algorithms, and multi-task scheduling. However, constrained by the unique underwater acoustic channel characteristics, UASNs barely satisfy these studies' requirements for timeliness, efficiency, and flexibility [6], [7]. We summarize various issues of the current UASNs in resource allocation, AI algorithms, and multi-task scheduling as follows:

Allocating appropriate resources lacks robustness and timeliness. Underwater acoustic channel quality is affected by harsh environments, varying over time and space [8], [9]. To accommodate such a dynamic underwater environment, allocating appropriate resources is essential to improve node and network performance. However, UASNs' unreliable communication constrains nodes from obtaining comprehensive channel and neighboring information, leading to potential deviated resource allocation results [10]. Meanwhile, directly altering resources based on such results reduces the robustness of UASNs. To rectify the deviated resource allocation, traditional UASNs require multiple adjustments to iterate the optimal solution. However, due to the long propagation delay (underwater sound speed of about 1500 m/s), the adjustments require long-term communication, leading to resource allocation untimeliness.

Multi-agent reinforcement learning (MARL) training lacks efficiency. MARL is a promising approach to address a variety of underwater tasks, such as multiple autonomous underwater vehicle (AUV) path planning, collaborative power allocation, and sensor data collection [10], [11], [12]. However, due to long propagation delay and low transmission rate, UASNs wait for a long time to receive the corresponding reward after each action, resulting in low training data collection efficiency. UASN nodes typically obtain observations through communication, but the high bit error rate (BER) due to the attenuation and noise can impair observations and thereby severely affect the action selection [13]. Moreover, the training data with impaired observations

are unacceptable for MARL algorithms, further exacerbating the data scarcity. In addition, long training time indicates extensive data communications that consume excessive energy, reducing the network lifetime.

Multi-task scheduling lacks flexibility. As the demand for underwater applications grows, one network needs to serve multiple tasks. Nowadays, researchers typically deploy large-scale, node-heterogeneous networks to tackle multi-task scenarios [14]. To simplify multi-task scheduling and reduce inter-task conflicts, some existing methods divide one network into various subnets, and each subnet performs an individual task. However, such an approach rigidifies the network topology, and each node is constrained into a preconfigured subnet. Under such a condition, a subnet may have idle nodes with excess energy while nodes in another subnet may exhaust all energy, which reduces the task efficiency and leads to unfair multi-task scheduling. Centralized scheduling is an alternative solution, but it requires obtaining the detailed status of all nodes through underwater acoustic communication, which costs considerable time and energy [15].

In summary, the inherent communication latency, data scarcity, and high operational cost of UASNs hinder advances in resource allocation, AI algorithms, and multi-task scheduling. Fortunately, digital twin (DT) is an appealing technology that can assist UASNs in tackling the above issues. DT emerges as an experimental technology that replicates the elements, functions, operations, and dynamics of physical systems in the digital world, allowing better control over testing, analysis, prediction, and damage prevention [16]. By creating a high-fidelity digital replica of the UASNs, DT can reflect the real network status in real time and offer a virtual test environment, effectively reducing communication latency, alleviating data scarcity, and minimizing the cost of trial and error [17]. In addition, DT can also implement control of physical entities in real UASN to achieve a bidirectional closed-loop feedback process of dynamic information [18]. However, empowering UASNs with DT presents several challenges, as detailed below:

(a) *Complexity of DT architecture.* Due to diverse devices, topologies, and protocols, UASN's performance is affected by the configurations of both node (such as power and sending rate) and network (such as routing tables and time slot allocation) [19]. However, UASN node and network differ in the domain, data amount, and controllable resources, thus DTs for them require different customized construction and control methods. A single-layer DT architecture, which simultaneously handles node and network in the same methods, struggles to address their diversity. Such an architecture fails to achieve accurate UASN replication, resulting in weak control of real UASN and poor maintainability of DT.

(b) *Consumption for constructing DT.* DT construction requires long-term communications to obtain massive real network data, which costs considerable time and energy, reducing the network lifetime [20]. Although low-frequency real-time data collection can conserve resources, but it reduces the fidelity of DT.

(c) *Incompatibility of UASNs methods to DT.* Compatibility of DT, UASN, and specific UASN studies is a necessary prerequisite for improving the UASN performance. However,

existing UASN studies are designed only for real UASN and lack interactions with DT, failing to directly implement in DT-based architecture.

To this end, we propose a Digital Twin-based intelligent Network Architecture (DTNA), which enhances UASN with strong environmental adaptability, intelligence, and multifunctionality. We discuss the main contributions as follows.

- 1) We propose a layered Digital Twin-based Network Architecture (DTNA) for UASNs, consisting of real network, local DT, and global DT. Local DT is constructed by extracting the local data of each node in the real network. Global DT is aggregated from local DTs. The layered design aligns with UASNs' data flow characteristics, simplifying the DT construction and maintenance, and improving the flexibility of control over the real network.
- 2) We develop a resource allocation paradigm in local DT (RAPD) to enhance the timeliness and robustness of existing resource allocation algorithms. RAPD realizes rapid perception across diverse performance metrics to infer environment change. Moreover, RAPD can prevent the UASN from employing deviant resources by iteratively evaluating and optimizing allocation schemes.
- 3) We propose a collaborative MARL framework in global DT (CMFD) to accelerate AI model training for collaborative tasks. In CMFD, agents decide strategies based solely on local observations without external information exchange and upload the decentralized transitions to global DT for training. CMFD can patch impaired data caused by node malfunction and communication faults. In addition, CMFD supplements extensive DT data to increase training data diversity.
- 4) We propose a task-oriented network slicing in global DT (TNSD) to assist multi-task scheduling methods with realizing flexible scheduling. TNSD unifies the decomposition and extraction of various task demands to adapt to heterogeneous application scenarios. Moreover, TNSD offers comprehensive network status in a cost-effective way, allowing task scheduling methods to rapidly obtain the detailed network status.

II. RELATED WORK

Due to the desire for UASNs with strong environmental adaptability, intelligence, and multifunctionality, extensive researches have been conducted on resource allocation, MARL algorithm design, and multi-task scheduling.

A. Resource Allocation

Existing underwater resource allocation studies are dedicated to appropriately allocate network and communication parameters. In [21] and [22], nodes estimate propagation delays to obtain the channel occupancy status, enabling appropriate temporal channel allocation to reduce collisions. [23] allows nodes to overhear the transmission schedules of neighbors to allocate time slots, realizing collision-free simultaneous transmission. [24] designed a hybrid non-orthogonal multiple access-based Multiple Access Control (MAC) protocol to jointly allocate transmission power and codebook, which achieves efficient

concurrent communication and optimizes energy consumption. [25] allows nodes to allocate power based on the signal strength of Request to Send (RTS) packets during the handshake phase, reducing energy consumption while ensuring successful transmission. [26] employs Deep Reinforcement Learning (DRL) to allocate time slots, which maximizes the network throughput without prior knowledge of propagation delays and transmission strategies.

B. MARL Algorithm

MARL has been widely utilized for underwater collaborative tasks such as target tracking, data collection, and power management [27]. [11] proposed an energy-efficient underwater multi-objective scheduling scheme for real-time AUV target hunting and environment searching, enabling AUVs to autonomously make decisions and collaboratively complete the collaborative task through limited information interaction. [28] proposed a MADDPG-based multiple AUVs trajectory planning algorithm that considers underwater obstacles and currents to maximize the collection rate and energy efficiency. [10] presented a distributed MARL-based collaborative power allocation approach to allocate the transmission power in a semi-cooperative way, achieving fair-effective communication and robustness. [29] implements multi-agent generative adversarial imitation learning from expert demonstrated trajectories, achieving formation control and obstacle avoidance for multiple autonomous underwater vehicles.

C. Multi-Task Scheduling

With the increasing demand for underwater applications, UASNs need to serve multiple tasks simultaneously. Existing researches on task scheduling primarily concentrate on demand extraction and execution optimization for single-type tasks, with minimal emphasis on collaborative scheduling for multiple tasks. [4] proposed a unified framework to schedule emergency and non-emergency tasks in multi-AUV data collection, which dynamically integrates the importance of cases and the accesses cost from the regional perspective, improving the applicability in a wide range of scenarios. [14] proposed a method for task-oriented intelligent networking demand extraction, which can provide personalized networking schemes according to the task type, satisfying the demand of different tasks on networking performance. [30] presented a task prioritization strategy based on a generic underwater task goal classification transformation, which divides the complex underwater operational tasks into generic task combinations and optimizes the resources consumption during the whole task. [31] presented a task allocation framework that can form an optimal AUV team for accomplishing critical missions, maximizing energy efficiency and guaranteeing mission completion within time constraint.

However, the practical implementation of the above studies in UASNs faces significantly serious challenges. Existing resource allocation methods tend to ignore the spatial and temporal variability of the underwater environment. The fixed allocation strategies relying on static information cannot handle dynamic

changes such as node drift, channel variations, and external interference, thus requiring reallocation of resources. Moreover, the packet loss due to high BER impairs the DRL-based methods' observation, resulting in inappropriate allocation schemes. The practical deployment of MARL also faces serious challenges. Due to the long propagation delay, low transmission rate, and high BER, MARL model training in the real network encounters challenges such as long interaction times, data scarcity, and data impairment. Considering the inefficiency of training data collection, existing underwater MARL algorithms rely on simulators for model training, which tend to be low confidence because their simulators often idealize the dynamic and severe acoustic communication environments. In existing multi-task scheduling methods, dividing the network into subnets for various tasks simplifies scheduling and reduces conflicts among tasks, but rigidizes the network topology and limits scheduling flexibility. Hindered by the high latency and energy scarcity, centralized scheduling that requires obtaining the global network status is not feasible. In conclusion, the current UASNs' architecture suffers from unique underwater characteristics, failing to satisfy the timeliness, efficiency, and flexibility as the existing UASNs studies requested.

D. Digital Twin Technology

To break the above bottlenecks, we introduce DT in UASNs, which is one of the enabling technologies in Internet of Things systems [32], [33], [34]. In recent years, DT technology has advanced rapidly, finding widespread applications in fields such as autonomous driving, computational offloading, and multi-UAV navigation. [35] leverages transfer learning to facilitate DT synchronization, and achieves optimal joint access network selection and power level allocation in DT-enabled internet of vehicles. [36] proposed a DT-empowered Mobile Edge Computing (MEC) framework, which empowers edge nodes with intelligence to achieve safe, efficient, and intelligent Connected and Automated Vehicle (CAV) lane-changing. [37] proposed a DT-enabled DRL training framework where the DRL model learns from DT, solving the inefficiency of data collection faced by the real-world UAVs.

In these studies, DT provides high-fidelity replica for various internet applications, enabling global observation, low-cost trial and error, and trend prediction. Based on the above advantages, DT is promising to deal with UASN studies' constraints of untimeliness, inefficiency, and inflexibility. Therefore, we design the DTNA to assist UASNs' development.

III. DIGITAL TWIN-BASED NETWORK ARCHITECTURE FOR UASNS

In this section, we propose DTNA to address the various limitations encountered by current UASNs. As shown in Fig. 1, our proposed DTNA integrates three layers: real network, local DT, and global DT.

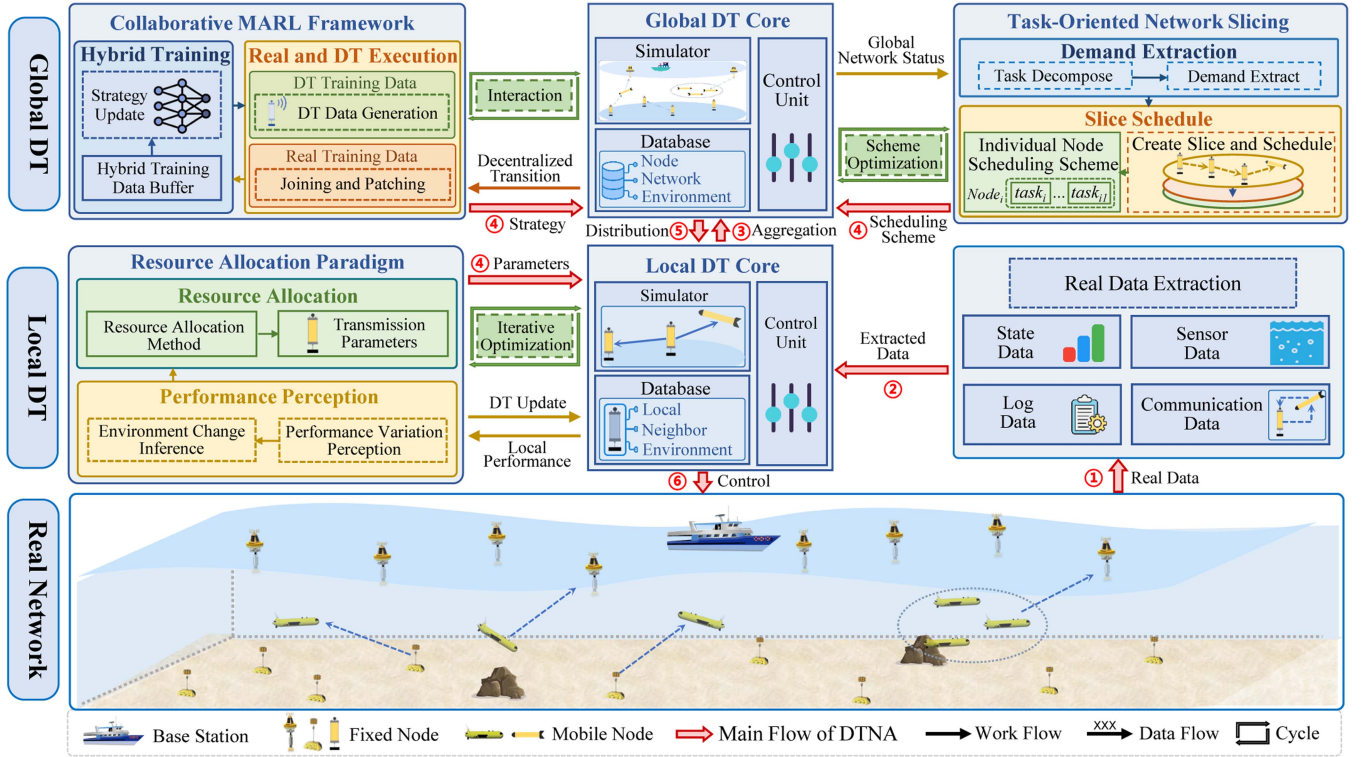


Fig. 1. Framework of DTNA. DTNA consists of real network, local DT, and global DT. Local DT extracts the local data to construct the digital replica of the node's surroundings. Global DT is aggregated from local DTs, representing the overall network. We propose DT-empowered approaches to enhance the existing resource allocation, MARL, and multi-task scheduling methods, improving the environmental adaptability, intelligence, and multifunctionality of UASNs.

A. Real Network

The real network of DTNA comprises a set of surface nodes and underwater nodes. In the real network, all nodes are equipped with acoustic modems to communicate with each other for transmitting data packets or issuing commands. Nodes with sensors can collect the surrounding environmental information. Moreover, the mobile nodes are capable of mobile data collection, communication relaying, and network extension and recovery.

Based on the above description, the nodes in the real network generate various types of data during their lifetime:

- *State data* refers to the node's local transmission configuration and device status, such as transmission power and residual energy. For a mobile node, it also includes movement parameters such as speed and attitude.
- *Sensor data* refers to the local data obtained by various sensors equipped on the node, including temperature, conductivity, obstacles' location, current velocity, etc.
- *Communication data* reflects the transmission information within communication range, such as packet flow, propagation delay, signal-to-noise ratio, packet size, etc.
- *Log data* refers to the execution logs of the node's intelligent methods at runtime, like the transitions of MARL algorithms.

B. Local DT

Local DT of DTNA is lightweight and low-power, deployed on each node with computing capabilities. We propose RAPD

on local DT, which leverages monitoring and simulation capabilities to provide resource allocation algorithms with fast performance awareness and iterative optimization. Local DT realizes the digital replica of the node's surroundings, which is represented as the node's local, neighboring, and environmental information.

- *Local information* is extracted from state, communication, and log data, including node configuration, transmission parameter, and historical behavior. Local information is responsible for providing node state monitoring and historical behavior records. Moreover, it assists in trend prediction and method optimization.
- *Neighboring information* is extracted from sensor, communication and log data, including the neighboring nodes' transmission parameters, location, and historical behavior. Neighboring information provides performance evaluation and trend prediction with the neighboring behavior, link status, and network topology.
- *Environmental information* is extracted from sensor and communication data, including obstacle locations, channel quality indicators, currents, and so on. Environmental information provides the physical and acoustic characteristics of the surrounding environment to simulate the impact on the node's behavior.

C. Global DT

Global DT of DTNA is deployed on the central nodes, which are typically the sink node in data collection or the leader node

of mobile clusters. Because such nodes have sufficient energy and receive more data than other relay nodes, allowing for a comprehensive network knowledge. Global DT constructs a digital replica, capturing each node's state and behavior, network's topology and configuration, and environmental characteristics. CMFD patches real data and provides extensive DT data to accelerate AI model training for collaborative tasks. Moreover, TNSD extracts task demands as unified and rapidly provides a comprehensive network status at a low cost for multi-task scheduling methods.

In DT *aggregation*, each node uploads the local DT data to the central nodes. We design specific rules for different types of nodes to upload data due to their diversity in communication and energy. To avoid costly battery replacement, fixed sensor nodes piggyback DT data on normal data packets, rather than sending actively. In addition to the piggybacking way, sufficient-energy and high-performance nodes, like AUVs, actively upload local DT parameters based on the pre-configurations or commands. The *local*, *neighboring*, and *environmental* information in local DT are aggregated and organized into *node*, *network*, and *environmental* information in global DT, enabling it to construct and maintain the replica of the global network.

Maintaining the global DT does not solely rely on successful communication. The real network scales represented by each local DT overlap to some extent. Even if a local DT cannot upload data, the absent network portion is potentially supplemented by other local DTs. In addition, global DT can utilize historical information to predict the status of network areas that lack DT data. Therefore global DT achieves high-fidelity and robust replica of the real network.

D. Bidirectional Closed-Loop Work Flow

The real data from the real network is automatically uploaded to construct the local DT in the following way. State and sensor data are immediately uploaded whenever they are changed or updated during operation. Moreover, the nodes parse the communication data of the packets transmitted by neighbors and then uploads it. In addition, the intelligent methods equipped with real-time interfaces upload execution log data after making decisions.

All the uploaded real data is extracted to construct the local DT. Local DT construction involves no additional data exchange, with all operations performed locally. In contrast, global DT construction includes *aggregation* of all the packaged DT data from each local DT, in addition to collecting and extracting local real data.

Upon completion of the DT construction, local and global DT cores are capable of replicating and simulating the real network, providing high-fidelity spatio-temporal data of local/node, neighbor/network and environment. RAPD utilizes local DT core to conduct performance variation perception and environment change inference on the local, neighbor, and the surrounding environment information. This enables real-time rapid and accurate resource allocation. CMFD greatly accelerates AI model training by generating extensive high-fidelity DT data and distributes the trained task execution strategies to each node via global DT. With the high-fidelity network mirroring provided

by the global DT, TNSD can rapidly and cost-effectively obtain the global network status, facilitating flexible node scheduling across multiple tasks. TNSD distributes scheduling scheme to each node's local DT core via global DT, guiding its execution sequence across multiple tasks.

IV. RESOURCE ALLOCATION PARADIGM BASED ON LOCAL DT

In this section, we propose RAPD to enhance the environmental adaptability of resource allocation algorithms. As shown in Fig. 2, RAPD comprises three parts: local DT core, performance perception, and resource allocation.

A. Local DT Core for RAPD

Local DT core represents a digital replica of the node's surroundings, consisting of three components: control unit, database, and simulator.

Control unit is responsible for data processing, simulator driving, and scheme deployment. Control unit analyzes various extracted data from DT construction to obtain local, neighboring, and environmental information, which are stored in the database and updated based on the subsequent real-time data. In addition, control unit drives the simulator to provide performance evaluation or generate DT data as required by the intelligent methods in DT. Control unit can also assess whether the intelligent methods' schemes meet the demand and deploy them to the real network for execution.

Database stores the node's local, neighboring, and environmental information, allowing the real-time monitoring of the node's surroundings. It can provide real-time performance metrics based on the historical behavior in local information.

Simulator is the most critical part of the DT core. Simulator obtains the network status and environment information from the database to conduct performance evaluation or DT data supplementation as required by the control unit. Moreover, it can be dynamically configured to simulate unexpected situations to enhance the robustness of the intelligent methods. Simulator is capable of generating a variety of performance metrics to provide optimization proposals for the control over the real network. With the above features of the simulator, the local DT core is able to control and optimize the real network based on the high-fidelity replica, achieving the bidirectional influence between real and DT.

In RAPD, local DT core is able to provide the performance metrics for performance perception and the real-time node information for resource allocation. Local DT core can also evaluate the allocation schemes over the current network.

B. Performance Perception

To rapidly perceive performance degradation, we develop performance perception based on Long Short-Term Memory (LSTM) [38]. Moreover, RAPD can infer the specifics of external changes and internal failures based on LSTM and the local DT core.

Local DT core continuously collects various real-time performance metrics based on local and neighboring information, such as data success rate, throughput, energy consumption, and

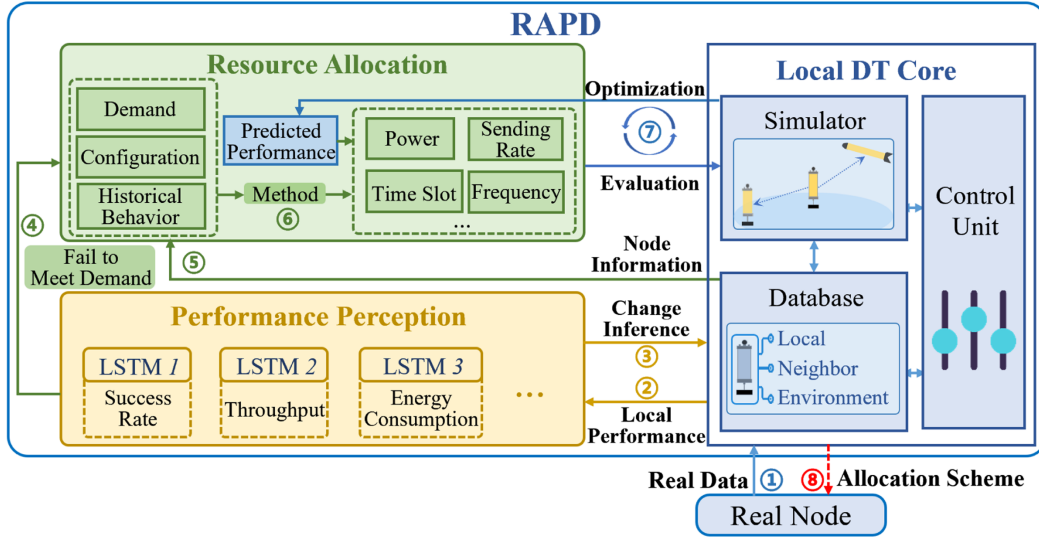


Fig. 2. Flowchart of RAPD. RAPD consists of local DT core, performance perception, and resource allocation. RAPD leverages the high-fidelity replica to rapidly perceive performance variations and iteratively optimize allocation scheme when performance metrics fail to meet demand.

so on. Such performance metrics over a historical period is input to the corresponding LSTMs to obtain the predicted performance expectations.

The LSTM is widely used for prediction, in which the LSTM cell is capable of storing historical sequential data and analyzing the temporal correlation. Each LSTM for performance perception is composed of several LSTM cells in series. LSTMs take the historical performance metrics $[W_{k-n,d}, W_{k-n+1,d}, \dots, W_{k-1,d}]$ as input, and generate the expected performance metrics $W_{k,d}^v$.

If the real performance metrics fall below the expectations by more than a certain threshold, it indicates internal failures or external interference beyond the current local DT coverage, which lead to a performance degradation. Internal failures can be rapidly distinguished because the local DT core monitors the real-time node state, while external changes require to be inferred by the local DT core. Based on the difference between the real performance metrics and expectations from LSTM, the local DT core simulates various external changes to evaluate the performance of the current allocation scheme, aiming for a high fitting between evaluated and real performance metrics to accurately infer external changes.

Finally, resource allocation is initiated to adjust network parameters to meet the demand.

C. Resource Allocation

RAPD does not define the specifics of the resource allocation algorithms, but provides a generalized model. Resource allocation makes preliminary schemes based exclusively on local information, and the schemes are iteratively evaluated and optimized by the DT core to obtain optimal results. The detailed process of resource allocation is described below.

First, local DT core delivers real-time node information to the resource allocation as input, including demand, configuration, and historical behavior. The demand refers to the minimum thresholds for performance metrics such as throughput, latency,

loss, and energy consumption, which are derived from the performance expectations and potential commands. The configuration indicates the node's local parameters such as power, bandwidth, and sending rate. It also contains neighboring information obtained from the particular observation. The historical behavior refers to the node's local transmission or movements over a historical period, as well as the observed neighboring behavior.

Then the resource allocation algorithm generates preliminary allocation scheme based on the available inputs from local DT core, which includes the node's parameters, such as power, time slots, and frequency. The preliminary scheme is delivered to the latest local DT core to conduct a spatial and temporal evaluation to obtain the predicted performance metrics. Next local DT iteratively fine-tunes and evaluates the scheme parameters to obtain the solution with best performance in the replication of the current local DT core.

Finally, local DT core deploy the optimal resource allocation scheme to the real network for execution.

V. COLLABORATIVE MARL FRAMEWORK BASED ON GLOBAL DT

In this section, we propose CMFD to accelerate AI model training for collaborative tasks, thus addressing the inefficiency of underwater MARL training. We do not qualify specific algorithm details, but propose an DT-based execution and training paradigm for collaborative tasks with discrete and continuous action spaces. As shown in Fig. 3, CMFD comprises three components: global DT core, real and DT execution, and centralized hybrid training.

A. Global DT Core for CMFD

Global DT core in CMFD offers a digital replica of the overall network. Same as local DT core, global DT core consists of three components: control unit, database, and simulator. Each component serves the same function as its counterpart in local DT core, with additional features. The control unit of global

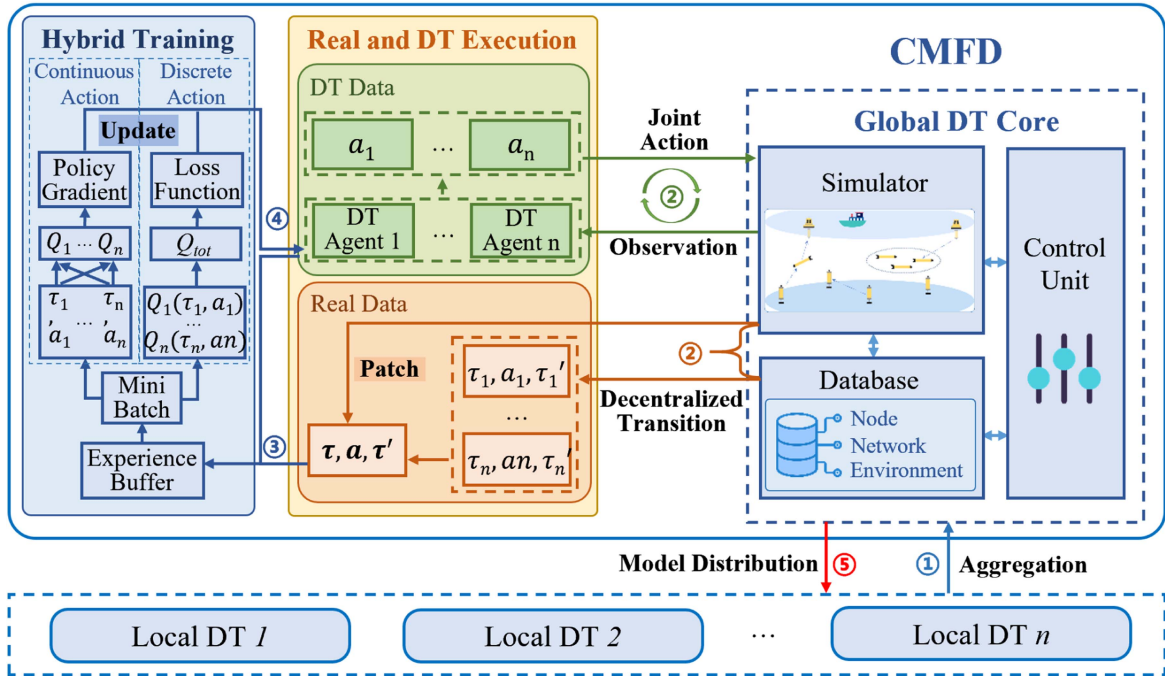


Fig. 3. Flowchart of CMFD. CMFD consists of global DT core, real and DT execution, and hybrid training. CMFD aggregates and patches scarce real data, and generates extensive DT data through global DT core's simulator. Finally, CMFD performs hybrid training based on such both types of data and distributes models to each local DT.

DT processes aggregated data and distributes AI models. The database differs slightly from that of local DT, which stores the *node*, *network*, and *environmental* information aggregated from the *local*, *neighboring*, and *environmental* information of each local DT.

In CMFD, global DT core is required to aggregate and patch the decentralized transitions. It also provides a high-fidelity network replica as an alternative interactive environment to rapidly generate extensive DT data in a low-cost way. Global DT core can extend network scenarios to simulate contingencies such as node malfunction and external interference, increasing the diversity of training data and enhancing the AI model's adaptability to unexpected situations.

B. Real and DT Execution

Real and DT execution refers to MARL algorithms interacting with real or simulated environments to make autonomous decisions and execute actions. It generates data for centralized model training.

For the mentioned underwater collaborative tasks such as target tracking and data collection, we model them as a Decentralized Partially Observable Markov Decision Process (Dec-POMDP), which is given by a tuple $G = \langle \mathcal{N}, \mathcal{S}, \mathcal{A}, P, \mathcal{R}, \mathcal{O}, \gamma \rangle$. Here $\mathcal{N} \equiv \{1, \dots, n\}$ denotes the finite set of agents and $s \in \mathcal{S}$ describes the true state of the environment. At each time step, each agent $i \in \mathcal{N}$ selects a discrete or continuous action $a_i \in \mathcal{A}$, forming a joint action $\mathbf{a} \in \mathcal{A} \equiv \mathcal{A}^n$. This results in a transition to the next state s' according to the state transition function $P(s'|s, \mathbf{a}) : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow [0, 1]$ and a team reward $r = \mathcal{R}(s, \mathbf{a})$. Due to the partial observability, each

agent $i \in \mathcal{N}$ draws an individual partial observation $\tau_i \in \mathcal{O}$ from the observation kernel $O(s, a)$. $\gamma \in [0, 1]$ is the discount factor, which indicates the long-term effect of the current action.

As shown in Fig. 4, each agent with *discrete* action space has a Deep Recurrent Q-network (DRQN), which receives the current local observation as input at each step and estimates its individual Q-value function $Q_i(\tau_i, a_i; \beta_i)$. Then agent chooses the action corresponding to the maximum Q-value. Each agent with *continuous* action space has a deterministic policy network $\mu_i(\tau_i; \beta_i)$, which receives the current local observation as input at each step and outputs a deterministic action.

Decentralized agents in local DTs do not have model update capability. To trade off exploration and exploitation, agents randomly choose actions with a probability of ϵ , and choose actions guided by models with a probability of $1 - \epsilon$. Each model in agent i chooses action a_i individually based on only local observation τ_i and gets next observation τ'_i . *Real transition* $\{\tau_i, a_i, \tau'_i\}$ is uploaded voluntarily to global DT in the initial training stage, but gradually evolves to be piggybacked by the normal data packets.

The decentralized transitions of all individually executed agents for each step are aggregated in global DT to generate joint transition $\{\tau, \mathbf{a}, \tau'\}$, where $\tau = \{\tau_i | i \in \mathcal{N}\}$ is the joint observation, $\mathbf{a} = \{a_i | i \in \mathcal{N}\}$ is the joint action of all agents, and $\tau' = \{\tau'_i | i \in \mathcal{N}\}$ is the next joint observation. τ and τ' in the joint transition may be impaired due to node failures, packet errors, and collisions. Global DT core patches the impaired transitions by utilizing the high-fidelity replica of the real work. Finally, the real joint transitions are stored into the experience buffer.

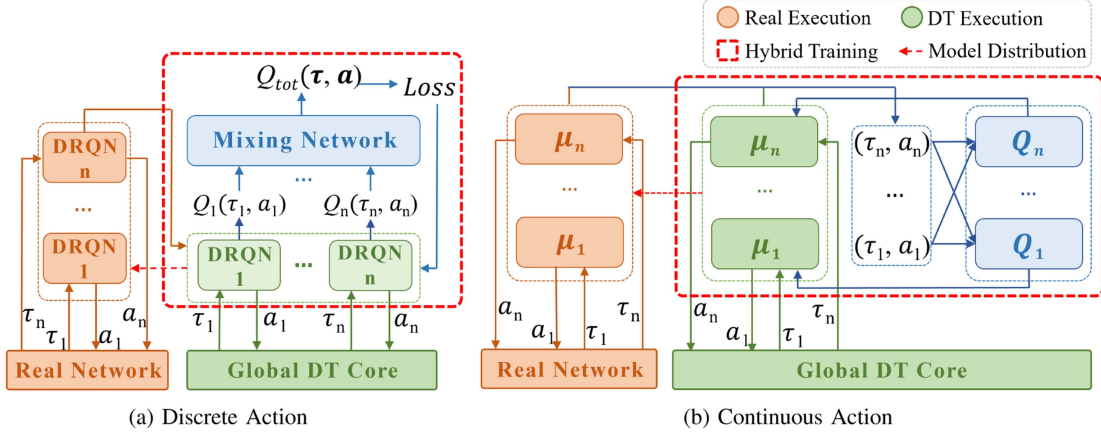


Fig. 4. Execution and training paradigm of MADRL models with discrete or continuous action space in CMFD.

Global DT in CMFD contains identical models with the same parameters as the decentralized agents. In DT execution, agents interact with global DT core's simulator to generate DT transitions. Each *DT transition* $\{\tau_i, a_i, \tau'_i\}$ is aggregated into joint transition $\{\tau, \mathbf{a}, \tau'\}$ and stored into the experience buffer. Real and DT transitions are stored indiscriminately in the experience replay buffer.

C. Centralized Hybrid Training

CMFD conducts centralized hybrid training in global DT, employing a hybrid of real and DT data to efficiently update each agent's model. We propose two training approaches for models with discrete and continuous action space.

1) Discrete Action Space

In the centralized hybrid training for models with discrete action space, we import a mixing network to aggregate individual Q-values from real or DT execution [39]. CMFD maximizes the aggregated Q-value while guaranteeing monotonicity of the aggregated and individual values, improving the global performance and interagent collaboration.

As shown in Fig. 4(a), the hybrid training consists of the mixing network and all DT DRQNs. In the training process, CMFD samples a batch of transitions $\{\tau, \mathbf{a}, \tau'\}$ from experience buffer and obtain all $Q_i(\tau_i, a_i)$ using DT DRQNs. The mixing network $f(\cdot)$ makes a mixture of all $Q_i(\tau_i, a_i)$ to produce the joint action-value function Q_{tot} as

$$Q_{tot}(\tau, \mathbf{a}) = f(Q_1(\tau_1, a_1), \dots, Q_n(\tau_n, a_n)). \quad (1)$$

Q_{tot} has the same monotonicity with the single agent value function as

$$\arg \max_{\mathbf{a}} Q_{tot}(\tau, \mathbf{a}) = \begin{pmatrix} \arg \max_{a_1} Q_1(\tau_1, a_1) \\ \dots \\ \arg \max_{a_n} Q_n(\tau_n, a_n) \end{pmatrix}. \quad (2)$$

The monotonicity can be enforced by imposing a constraint on the relationship between Q_{tot} and each Q_i as

$$\frac{\partial Q_{tot}(\tau, \mathbf{a})}{\partial Q_n(\tau_i, a_i)} \geq 0, \quad \forall n \in \{1, 2, \dots, N\}. \quad (3)$$

To guarantee (3), we use a hypernetwork to generate nonnegative parameters as the weights W_i of the mixing network. The hypernetwork takes the global network state s as input, which is inferred from τ by global DT core. Biases b_i of the mixing network are generated similarly, but can be negative.

The DRQN agents in global DT are trained end-to-end to minimize the following loss

$$Loss(\theta) = \frac{1}{b} \sum_{j=1}^b \left(y_{tot}^j - Q_{tot}(\tau^j, \mathbf{a}^j; \theta) \right)^2, \quad (4)$$

$$y_{tot} = r + \gamma \max_{\mathbf{a}'} Q_{tot}(\tau', \mathbf{a}'; \theta^-), \quad (5)$$

where b is the batch size, γ is the discount factor, θ is the parameters of the evaluation network, θ^- is the parameters of the target network. θ of the evaluation network is updated by minimizing (4). θ is assigned to θ^- every certain episodes, otherwise it stays unchanged between individual updates.

2) Continuous Action Space

In the centralized hybrid training for models with continuous action space, we import value networks for each policy network to incorporate information from other agents, allowing for a better understanding of the others' behavior and thus achieving better collaboration [40].

As shown in Fig. 4(b), the hybrid training consists of all DT policy networks and the corresponding value networks. In the training process, CMFD samples a batch of transitions $\{\tau, \mathbf{a}, \tau'\}$ from experience buffer. The centralized value network Q_i is trained to minimize the following loss

$$Loss(\theta_i) = \frac{1}{b} \sum_j \left(y^j - Q_i^\mu(\tau^j, a_1^j, \dots, a_N^j) \right)^2, \quad (6)$$

$$y^j = r^j + \gamma Q_i^{\mu'}(\tau'^j, a_1', \dots, a_N') \Big|_{a'_k = \mu'_k(\tau_k^j)}, \quad (7)$$

where $\mu = \{\mu_1(\tau_1; \phi_1), \dots, \mu_n(\tau_n; \phi_n)\}$ is the set of all agents' current policy networks with parameter ϕ_i , b is the batch size, γ is the discount factor. $Q_i^\mu(\tau^j, a_1^j, \dots, a_N^j)$ is a centralized action-value function that takes the joint action $\mathbf{a} = \{a_i | i \in N\}$

Algorithm 1: Centralized Hybrid Training.

```

1: Get the experience reply buffer  $D$ ;
2: Set the learning rate  $\alpha$ ; set the discount factor  $\gamma$ ;
3: for  $train \leq trainstepmax$  in each epoch do
4:   Sample a batch of hybrid DT and real transitions;
5:   if discreteactionspace then
6:     Get each DT agent's DRQN  $\theta$  and target DRQN  $\theta^-$ ;
7:     Update the DRQN by minimizing the loss as (4);
8:     if  $update - interval$  train then
9:        $\theta^- = \theta$ ;
10:    end if
11:  end if
12:  if continuousactionspace then
13:    Get value network  $\theta$  and target value network  $\theta^-$  from Global DT;
14:    Get each DT agent's policy network  $\phi$  and target policy network  $\phi^-$ ;
15:    Update value network by minimizing the loss as (6);
16:    Update policy network using the policy gradient as (8);
17:    if  $policy - update - interval$  train then
18:       $\phi^- = \phi$ ;
19:    end if
20:    if  $value - update - interval$  train then
21:       $\theta^- = \theta$ ;
22:    end if
23:  end if
24: end for

```

and the joint observation $\tau = \{\tau_i | i \in N\}$ as input, and outputs the Q-value for agent i .

The policy network of each agent i in global DT can be updated by calculating the policy gradient as

$$\nabla_{\phi_i} J = \frac{1}{b} \sum_j^b \nabla_{\phi_i} \mu_i \left(\sigma_i^j \right)$$

$$\nabla_{a_i} Q_i^\mu \left(\tau^j, a_1^j, \dots, a_N^j \right) \Big|_{a_i = \mu_i(\tau_i^j)}, \quad (8)$$

$$\phi_i = \phi_i + \alpha \nabla_{\phi_i} J(\pi), \quad (9)$$

where $\mu = \{\mu_1(\tau_1; \phi_1), \dots, \mu_n(\tau_n; \phi_n)\}$ is the set of all agents' current actor network with parameter ϕ_i . ϕ_i of the actor network is updated according to (9).

The centralized hybrid training of CMFD is detailed in Algorithm 1. Global DT core can evaluate whether the centralized hybrid training is converging. After obtaining the optimal collaborative strategy, global DT distributes the model parameters to the local DTs in each decentralized node. The complete execution stages of CMFD are shown in Fig. 5.

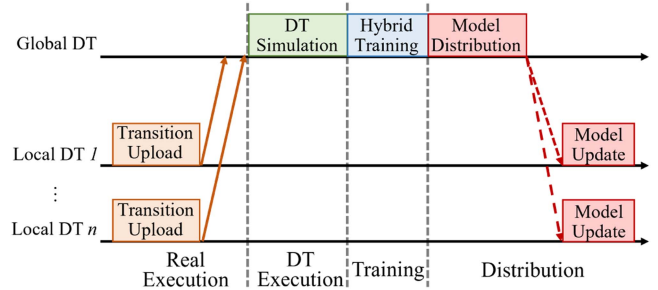


Fig. 5. Timeline of CMFD execution stages.

VI. TASK-ORIENTED NETWORK SLICING BASED ON GLOBAL DT

In this section, we propose TNSD to improve the flexibility of multi-task scheduling algorithms. As shown in Fig. 6, TNSD comprises three components: global DT core, demand extraction, and slice schedule.

A. Global DT Core for TNSD

TNSD and CMFD share a common global DT core, but each emphasizes different functionalities. In addition to aggregating each local DT to construct a digital network replica, the control unit of TNSD also consistently monitors the timeliness of the network scales represented by each local DT. The control unit drives the simulator to predict events in network scales that lack local DT data, such as node drift, energy exhaustion, mobile node joining.

In TNSD, global DT core is required to provide the current global network status and predict network trends. In addition, global DT core can evaluate the slice schemes spatially and temporally to obtain the corresponding performance for scheme optimization.

B. Demand Extraction

Demand extraction is responsible for task decomposition and demand extraction. Heterogeneous tasks differ significantly in emphasis on communication, detection, and navigation, which have diverse resource demands. To unify and simplify task demand extraction, we decompose heterogeneous tasks into three subtasks: communication, detection, and navigation.

The new task is delivered to TNSD for decomposition and then converted into a raw task matrix $RT = [rt_{com}, rt_{det}, rt_{nav}, ST]$ to abstract the task characteristics. Each type of subtask corresponds to a specific rt as

$$rt_{com} = [source, destination, size, number, \dots],$$

$$rt_{det} = [location, scale, duration, urgency, \dots],$$

$$rt_{nav} = [destination, pathway, timing, \dots], \quad (10)$$

where each rt contains the essential parameters of the subtask to support the demand extraction. ST is the scheduling timeline of the task, which indicates the scheduling of the three subtasks

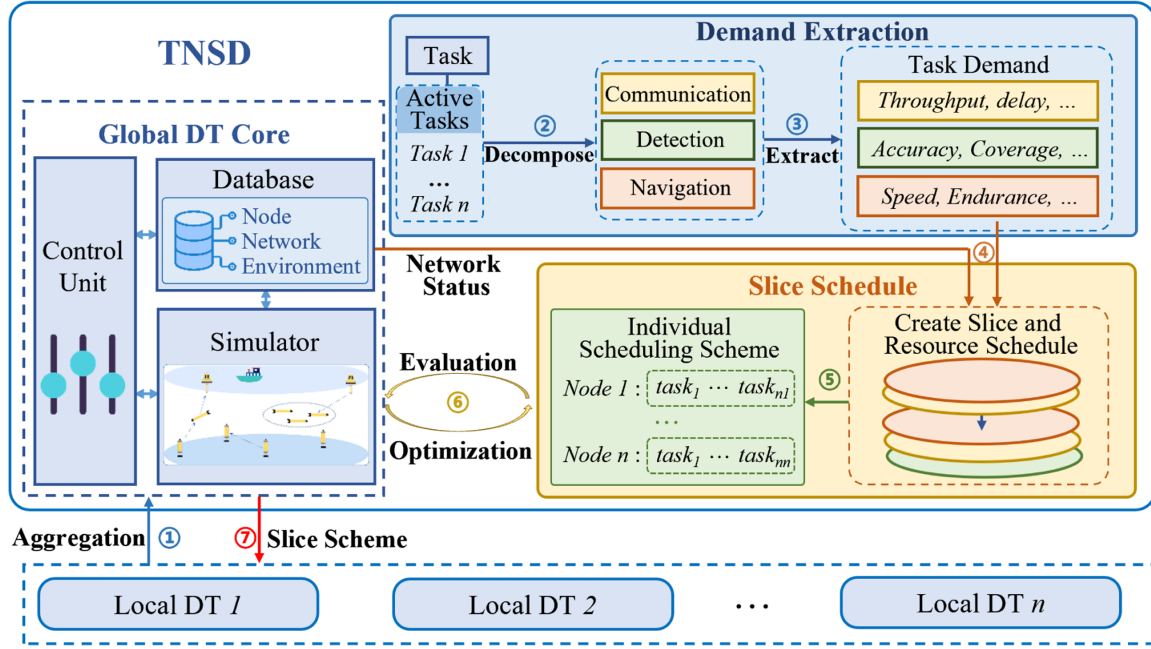


Fig. 6. Flowchart of TNSD. TNSD unifies heterogeneous task demand extraction and rapidly provides a comprehensive network status in a cost-effective way. TNSD creates slice and schedules resources accordingly, and then the network slices are converted into individual node scheduling schemes, which are distributed to each local DT for execution.

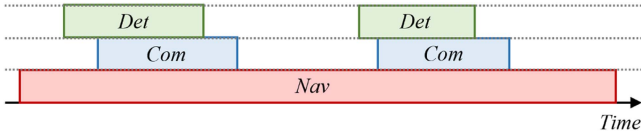


Fig. 7. The scheduling timeline ST of a cruise task. Nodes navigate on a specified path (Nav), detect in alert areas (Det), and upload detection data (Com).

over the entire task lifetime. ST is represented as

$$ST = \begin{bmatrix} st_{com} \\ st_{det} \\ st_{nav} \end{bmatrix} = \begin{bmatrix} [s_1, e_1], \dots, [s_i, e_i], \dots \\ [s_1, e_1], \dots, [s_i, e_i], \dots \\ [s_1, e_1], \dots, [s_i, e_i], \dots \end{bmatrix}, \quad (11)$$

where $[s_i, e_i]$ is the start and end time of the i -th execution period of a subtask. The subtask has an uncertain number of execution periods. An instance of ST is shown in Fig. 7. The cruise task requires the mobile node to patrol back and forth on the specified path, detect in the designated area, and transmit data to the buoy node.

We extract the task demand based on the rt matrix of each subtask and historical task execution data. The demand extraction method is not specifically quantified, but there are a variety of ways to realize it, such as LSTM, Particle Swarm Optimization (PSO) algorithm and so on. RT is input to the demand extraction method to obtain the task demand matrix TD , which contains the task demand td of each subtask. The task demand td can be categorized into three types, corresponding to the three types of tasks, represented as

$$td_{com} = [throughput, delay, loss, \dots],$$

$$td_{det} = [accuracy, coverage, update_rate, \dots],$$

$$td_{nav} = [speed, endurance, secrecy, \dots], \quad (12)$$

where the three types of subtasks have performance demands in diverse metrics.

C. Slice Schedule

Slice schedule is responsible for task slices resource schedule according to task demand matrix TD and the global network status.

Global DT core aggregates local DTs to obtain the local state and task scheduling of each node, enabling to obtain the current global network status and predict network trends both temporally and spatially through the simulator. We obtain the network status matrix $NS = [ns_1, \dots, ns_i, \dots, ns_n]$ from the global DT core, where n is the number of all nodes, ns_i indicates the state of the i -th node, along with the tasks currently executed by the i -th node, represented as

$$ns_i = [nodeid, location, speed, \dots, tasks], \quad (13)$$

where $tasks$ refers to the set of tasks executed by the node.

When a new task demand matrix TD is produced, TNSD creates task slices corresponding to its subtasks and then conducts resource schedule for the slices based on NS . TNSD utilizes the specific optimization algorithm to seek the slice resource schedule solution and finally generates the slice resource schedule matrix RS for each subtask as

$$RS = [node_1, \dots, node_i, \dots, node_n], \quad (14)$$

$$node_i = [location, speed, \dots, role, duration],$$

$$role \in \{source, sink, relay, leader, member, \dots\}, \quad (15)$$

where $node_i$ indicates the state, role, and duration of the i -th node in the slice.

We obtain each individual scheduling scheme ins of all nodes by combining the RS of each slice. The individual scheduling scheme ins_i of the i -th node is represented as

$$ins_i = [task_1, \dots, task_{ni}]$$

$$= \begin{bmatrix} role_1 & \dots & role_{ni} \\ duration_1 & \dots & duration_{ni} \\ \vdots & \ddots & \vdots \\ status_1 & \dots & status_{ni} \end{bmatrix}, \quad (16)$$

where ni is the number of tasks executed by node i . The ins indicates the node's task execution sequence, including the role, duration and status in the task, which is utilized to concretely instruct the node to perform the tasks.

We need to determine the network configuration for task slices, such as MAC, routing, power, frequency, etc. The network configuration is initially assigned based on previous experience and are iteratively evaluated and optimized by the simulator in conjunction with all ins . Finally, the optimal task slice scheme is distributed to each local DT.

VII. PERFORMANCE EVALUATION

In this section, we evaluate the performance of our proposed DTNA. To our knowledge, there is no comparable research works on underwater digital twin network architecture. Thus we evaluate the enhancement effect of DTNA on the existing underwater methods. We evaluate some existing works on underwater resource allocation, MARL algorithms, and multi-task scheduling. Then we further integrate these works with DTNA and compare them to the original methods to evaluate the performance improvements enabled by DTNA on existing works. First, we test the DT fidelity using real devices. Based on this experimental setup, we evaluate the timeliness and robustness improvement of RAPD on resource allocation algorithms. Moreover, we utilize a simulation environment to evaluate the acceleration of CMFD on MARL training, and the cost-effectiveness of TNSD on network status obtainment.

For the DT core, we implement the control unit and database using Python and implement the simulator using the improved AquaSim-Tg [41]. We develop interfaces for the nodes' device, protocol stack, and intelligent methods, connecting them to the control unit to facilitate real-time data acquisition.

A. DT Fidelity Test

We conduct a lab pool test to evaluate DT fidelity. As shown in Fig. 8, we deploy three acoustic modems as transmission nodes and one acoustic modem as an interference source in the pool. The initial main parameters of the nodes are shown in Table I [42], [43]. The transmission nodes adopt static routing and Pipelining MAC (PMAC) protocol for communication [44]. To avoid packet collisions among the three transmission nodes, we set the slot cycle of the PMAC to 3. The transmission rate, preamble delay, and guard time are set based on the actual

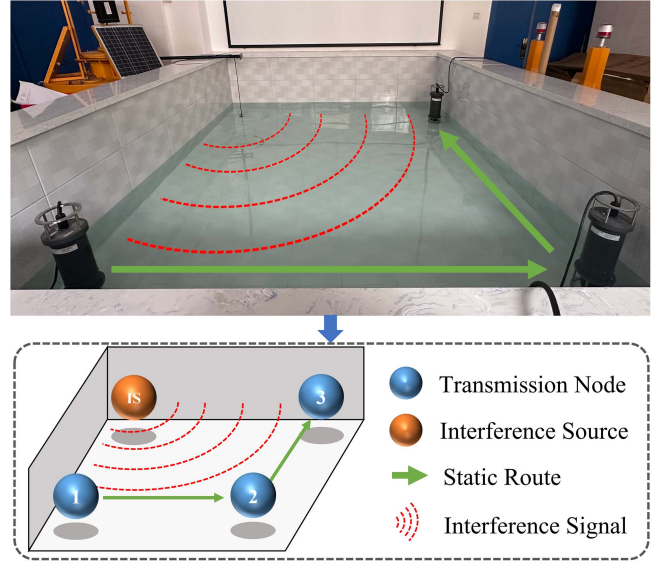


Fig. 8. DT fidelity test scenario. Node 1 and 2 are data sending nodes. Node 3 is the sink node. Interference source sends the interference signal to simulate channel quality degradation.

TABLE I
INITIAL TRANSMISSION PARAMETERS

Parameters	Values	Parameters	Values
Slot Length	6 s	Transmission Rate	1500 bps
Packet Size	400 Bytes	Preamble Delay	0.5 s
Slot Cycle	3	Guard Time	0.05 s
Static Route	1→2→3	Sending Rate	0.03

TABLE II
THE DETAILS OF DYNAMIC CHANGES

Timing	Parameter	Change
500s	Sending Rate	from 0.03 to 0.08
1000s	Packet Size	from 400 B to 200 B
1500s	Slot Length	from 6 s to 4 s
2000s	Channel Quality	Active Interference Source

performance of the acoustic modems [42]. The slot length is determined by the sum of transmission and propagation delay. We calculate the transmission delay of 200B and 400B packets to be 1.817s and 3.133s based on the transmission parameters setup. The propagation delay is calculated to be 2s using a typical underwater communication distance of 3km and a sound speed of 1500m/s [43]. Finally, we add the transmission and propagation delay, and round up to obtain the corresponding time slot lengths of 4s and 6s for 200B and 400B packet lengths.

We conduct dynamic changes in time slot length, packet size, sending rate, and channel quality, in which the channel quality change is simulated by the additional acoustic modem to send interference signal. The details of dynamic changes are shown in Table II. We deploy local DT on each transmission node and global DT on node 3. We test the DT perception of dynamic changes and verify the DT fidelity by comparing the DT performance simulation results with the real performance.

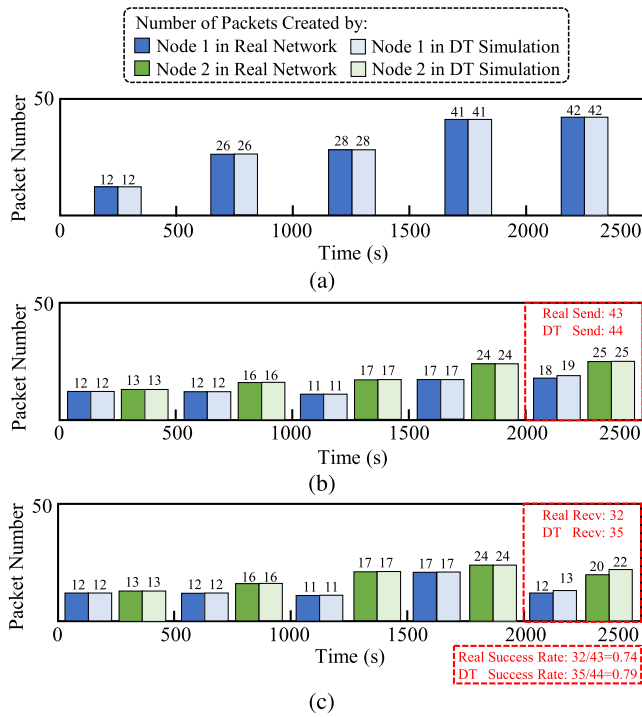


Fig. 9. Number of packets sent/received in each real node and local DT at various time ranges: (a) number of packets sent by Node 1; (b) number of packets sent by Node 2; and (c) number of packets received by Node 3.

Fig. 9 shows the number of packets sent or received in each real node and local DT, which can infer the data traffic and congestion. It can be observed that each local DT has a high degree of fitting with the real node in the number of packets sent or received. Specifically, the increase in the sending rate at 500s maximizes the number of packets sent and causes packet congestion, since there are always packets waiting to be sent at each time slot. Moreover, the packet congestion in node 2 also causes it to send more packets created by node 2 rather than relaying packets created by node 1. The packet size change at 1000s does not affect the sending strategy or the number to be sent. However, we can observe that difference in the number of the two types of packets sent by node 2 increases, indicating that the packet congestion becomes increasingly severe over time. The slot length reduction at 1500s relieves packet congestion and increases packet traffic.

After the channel quality decreases at 2000s, the DT packet numbers are slightly higher than the real ones. This is because the local DT needs to analyze several failed communications to evaluate the packet loss probability. In addition, we calculate the transmission success rate from the numbers of packets sent by node 2 and received by node 3 as shown in Fig. 9(b), (c). It can be observed that the DT transmission success rate is close to the real value. In conclusion, the local DT rapidly perceives the dynamic changes and accurately simulates up to 99% of the nodes' transmission packet numbers after each change, achieving a high-fidelity replica of the nodes' transmission.

Fig. 10 shows the throughput of the real network and global DT. It can be observed that the global DT realizes real-time

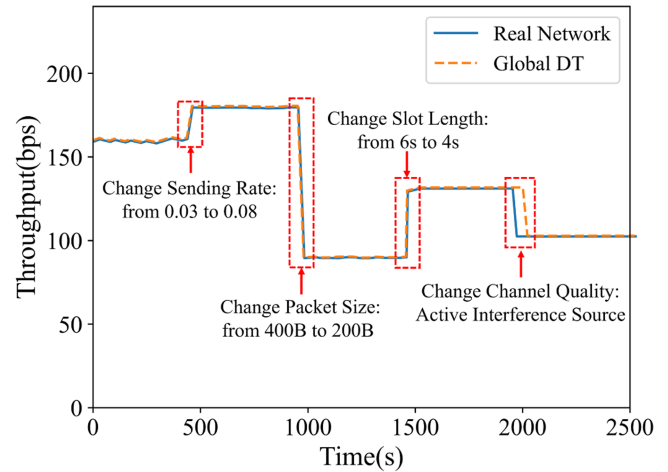


Fig. 10. Throughput of the real network and global DT.

perception of throughput variations to dynamic changes in sending rate, data packet size, time slot length, and channel quality. It should be noted that after significantly increasing the sending rate, the throughput increases slightly. This is because the sending rate of 0.03 makes the network throughput close to the theoretical upper limit at the current slot length, so increasing the sending rate fails to greatly increase throughput and instead congests the packet queue. After the channel quality decreases, the global DT's throughput is slightly delayed compared to the real network. Similar to local DT, this is because the global DT needs time to evaluate the packet loss probability. In brief, the global DT realizes the network throughput perception and simulates to each dynamic change. The global DT accurately simulates the real network throughput over 98% of the whole network lifetime, achieving a high-fidelity network replica.

Limited by the size of the laboratory pool and the expensive cost of the real acoustic modems, we adopt only a relatively small number of nodes to conduct global DT fidelity test. To complement the high fidelity of our proposed DTNA under large-scale networks, we perform simulation tests for up to 30 nodes in Section VII-D.

B. Timeliness and Robustness Test for RAPD

Based on the DT fidelity lab pool test, we conduct test to evaluate the timeliness and robustness improvement of RAPD on the selected resource allocation algorithm. In the test scenario as shown in Fig. 8, we shut down node 2 and allow the node 1 and 3 to alternately send 200B packets at a 4s time slot, thus to duplicate a partial data sending and receiving in the large-scale network. Moreover, the size of a header-only RTS packet is 30B and the highest transmission power of the acoustic modems is 30W. The interference source continuously sends random signals at varying power to simulate the interfering acoustic entities.

We select the Power Control based handshake-competition MAC (PC-MAC) and PC-MAC-Relink (improved PC-MAC, PC-MAC-R) as the baseline, and use PC-MAC assisted by RAPD (PC-MAC-DT) for comparison [25].

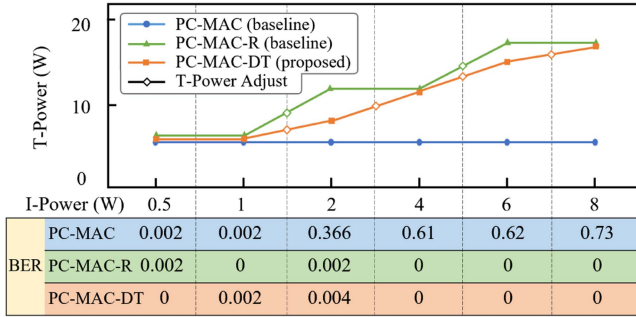


Fig. 11. T-Power adjustment and BER performance against varying I-Power. T-Power refers to the the transmission node power. I-Power refers to the interference source power. BER refers to the bit error rate.

- 1) *PC-MAC (baseline)* allows nodes to send RTS at the highest transmission power at the handshake stage, and the receiving nodes calculate the minimum transmission power of the current communication channel based on the signal strength of the received RTS, which is used as the fixed transmission power for the subsequent communication.
- 2) *PC-MAC-R (baseline)* also uses the handshake strategy to determine the transmission power. However, we have improved PC-MAC-R, which can re-handshake to determine an appropriate transmission power after the BER exceeds the set threshold, thereby restoring the communication link.
- 3) *PC-MAC-DT (proposed)* leverages local DT to perceive data and interference signal strength. When the BER is excessive to meet the demand, PC-MAC-DT evaluates the channel quality based on the historical signal strength, and determines the appropriate power by iterative optimization.

We test the BER performance of the three methods against dynamic interference power variations. And we also evaluate the adjustment time and energy consumption required by each method to restore communication.

Fig. 11 shows the transmission power adjustment and BER performance of the three methods against dynamic interference power variations. It can be observed that the BER of PC-MAC increases with I-Power. This is because PC-MAC determines the fixed transmission power in advance during the handshake stage, but the fixed power only adapts to small channel quality fluctuations. Moreover, we can observe that both PC-MAC-R and PC-MAC-DT can dynamically adjust the T-power to maintaining a low BER.

Table III demonstrates the cost of power adjustment and the energy efficiency of subsequent data transmission across various methods. PC-MAC-R re-handshakes to determine an appropriate transmission power to restore communication. However, PC-MAC-R has a long adjustment time and high energy consumption, this is because the re-handshake requires additional control packets, which increases communication overhead. In addition, we can observe that PC-MAC-DT has a low time and energy consumption while maintaining a low BER. PC-MAC-DT can perceive the signal-to-noise ratio of the received

TABLE III
COSTS AND EFFECTS OF T-POWER ADJUSTMENT

	I-Power(W)	0.5	1	2	4	6	8
PC-MAC-R (baseline)	T-Power(W)	6	6	6→12	12	12→18	18
	A-Time(s)	/	/	8	/	8	/
	A-Energy(J)	/	/	43.1	/	54	/
	Energy/pkt(J)	10.9	10.9	21.8	21.8	32.7	32.7
PC-MAC-DT (proposed)	T-Power(W)	6	6	6→8	8→12	12→16	16→18
	A-Time(s)	/	/	0.1	0.1	0.1	0.1
	A-Energy(J)	/	/	0	0	0	0
	Energy/pkt(J)	10.9	10.9	14.5	21.8	29	32.7

Note: A-Time and A-Energy refer to the time and energy cost to adjust power to restore communication. Energy/pkt refers to the energy used for per successful packet transmission at the current T-Power.

packets to evaluate the noise level of the interference source, and utilize the local DT to select the appropriate power to guarantee communication quality. The locally executed resource allocation of PC-MAC-DT eliminates time and energy costs for additional control information exchanges. Moreover, PC-MAC-DT selects lower power while guaranteeing communication compared to PC-MAC-R, achieving higher allocation accuracy and energy efficiency for subsequent data transmission.

In conclusion, PC-MAC-DT outperforms PC-MAC and PC-MAC-R in adjustment time, energy consumption, and allocation accuracy. PC-MAC-DT can adjust the transmission power at almost 0 overhead, maintaining a BER close to 0 against interference. In addition, it improves the energy efficiency of subsequent transmissions by approximately 10% compared to PC-MAC-R. The above demonstrates that RAPD exhibits improved timeliness and robustness.

C. Acceleration Test for CMFD

Due to the limitations of the field and equipment, we conduct the simulation test to evaluate the acceleration of CMFD on MARL training by utilizing a simulated environment with actual sound speed data instead of a lab pool. The simulation environment is implemented by integrating Python and AquaSim-Tg, which can emulate the underwater acoustic channel by bellhop to calculate the propagation signal loss under multiple factors, such as attenuation, noise, multipath, and temporal and spatial variability due to transmitter/receiver motion. The computer configurations are given as follows: *AMD 5995WX* CPU, *NVIDIA RTX 4090* GPU.

Similar to the real network in Fig. 1, we consider a multi-AUV collaborative data collection task, where multiple AUVs are deployed to collect sensor data from each sensor node (SN) on the seabed. AUVs require intelligent trajectory planning algorithms to maximize data collection rates and energy efficiency. Time is equally divided into fixed slots. In each slot, each AUV broadcasts state for exchanging collaborative information, and selects the velocity and target SN according to the trajectory planning algorithm. We consider four data collection scenarios in a 5 km × 5 km area with different numbers of AUVs and SNs as shown in Table IV, where SNs are randomly deployed.

We adopt Data Collection scheme for Multi-modal underwater sensor networks based on Deep reinforcement learning

TABLE IV
COLLECTION RATE AND TRAINING TIME OF DCMD AND DCMD-DT IN FOUR SCENARIOS

Scenario	Number of AUVs	Number of SNs	Algorithm	Real Episodes	DT Episodes	Collection Rate	Training Time
I	2	20	DCMD (baseline)	40000	/	63.15%	1.1×10^5 h
			DCMD-DT (proposed)	15	70000	62.89%	3.78h
II	3	20	DCMD (baseline)	60000	/	70.68%	1.5×10^5 h
			DCMD-DT (proposed)	12	90000	71.76%	3.76h
III	3	25	DCMD (baseline)	60000	/	71.32%	1.54×10^5 h
			DCMD-DT (proposed)	12	90000	71.81%	3.76h
IV	4	25	DCMD (baseline)	80000	/	73.24%	1.8×10^5 h
			DCMD-DT (proposed)	9	120000	73.76%	3.11h

(DCMD) as the baseline and utilize DCMD assisted by CMFD (DCMD-DT) for comparison [28].

- 1) *DCMD (baseline)* is a MADDPG-based multiple AUVs trajectory planning algorithm for underwater data collection. DCMD guides AUVs to select appropriate velocity and target SN considering underwater obstacles and currents, to maximize collection rate and energy efficiency.
- 2) *DCMD-DT (proposed)* has the same model design as DCMD. However, DCMD-DT requires each AUV not only to perform data collection but also to observe obstacle locations and environmental data such as ocean currents, sound speed, and noise. Global DT constructs the high-fidelity replica of the data collection scenario based on these observations, providing sufficient DT data and patching the impaired real data.

DCMD interacts with the environment to simulate real execution until the model training converges. DCMD-DT training alternates between real execution epoch and DT execution epoch. The episode number of a real execution epoch is determined by the number of AUVs. The scenario with more AUVs requires fewer episodes to collect data to construct the global DT. According to [28], we set the hyperparameters of the DCMD and DCMD-DT as follows: actor/critic hidden layer neuron number 64, batch size 1024, discount factor 0.95, actor/critic learning rate 0.001.

Table IV shows the episode number of real execution and DT execution required for DCMD and DCMD-DT model training, as well as the collection rate and training time. It can be observed that the DCMD training time is extremely high, this is because DCMD utilizes real execution for model training and requires a large number of episodes to converge, which indicates the infeasibility of training directly in the real underwater environment. We can also observe that the training time of DCMD-DT is significantly reduced, less than 1% of the DCMD training time, because sufficient high-fidelity DT data from global DT accelerates the convergence of the models. DCMD-DT can construct the global DT with merely a few real execution episodes to collect environmental data, such as current and channel quality. This enables the utilization of DT execution to assist model training, significantly accelerating the model training. Moreover, DCMD and DCMD-DT have almost the same collection rate, which verifies the fidelity of the DT data.

In addition, we can observe that the final collection rates of the converged models fail to reach the desired values, because

DCMD utilizes a fixed communication strategy to collect data, which ignores the impact of the real ocean environment on communication, resulting in possible collection failures. CMFD accelerates model training, but cannot fix the inherent flaws of the model itself.

In conclusion, CMFD greatly accelerates model training by generating extensive high-fidelity DT data, reducing the training time to less than 1% of the real execution training. Moreover, CMFD trades off the scarce mobile and communication resources of the distributed nodes with the abundant computational resources of the central nodes, extending the network lifetime.

D. Resource Saving Test for TNSD

We conduct simulation test to evaluate the time and energy consumption of obtaining the global network status to evaluate the resources saving effect of TNSD.

The main scenario of TNSD is the large-scale, node-heterogeneous networks with multiple tasks. Therefore, we consider a large-scale network with communication, detection, and navigation capabilities, including multiple types of surface and underwater nodes.

- *Central Node* serves as the data sink node. It also collects node status and environmental information to issue commands for multi-task scheduling.
- *Buoy* serves as a cluster head node. It is responsible for forwarding data to the central node and forwarding commands to the underwater nodes.
- *SN* is responsible for monitoring the underwater environment. SNs need to upload data to buoys, and the transmission process may require multi-hop.
- *AUV* is responsible for navigation and detection, and can substitute for the data forwarding node when it fails.

We consider four multi-task scenarios in a $20\text{km} \times 20\text{km}$ sea area, containing 1 central node, 4 buoys, and varying numbers of SNs and AUVs. The specific node number and topology of the four scenarios are shown in Fig. 12. All nodes adopt the same transmission parameters as shown in Table V [42], [43], where the time slot length is determined by the sum of the maximum propagation delay between any neighboring nodes and the transmission delay of the largest data packet.

Multi-task scheduling requires obtaining the global status, including node information such as local state and carrying tasks, network information such as topology and routing, as well as

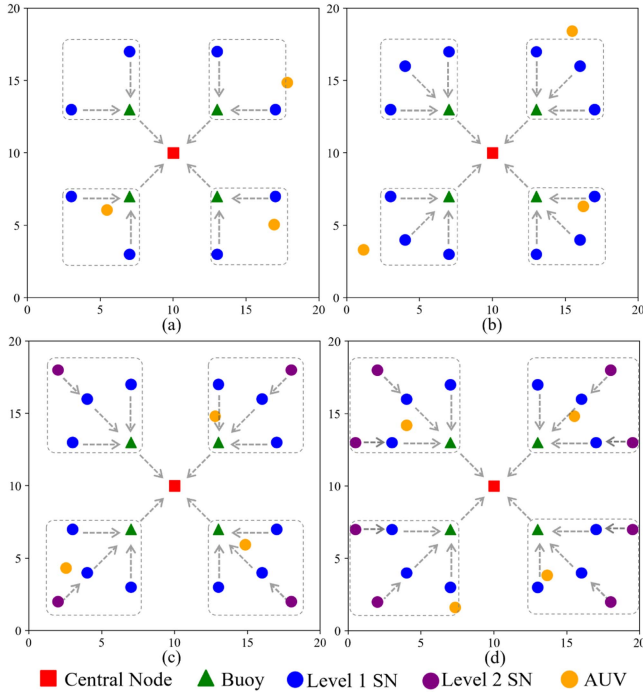


Fig. 12. Multi-task large-scale network scenarios. In the scenarios, the network is divided into four clusters where Buoys are the cluster head and SNs are the member. Central node is the data sink and conducts task scheduling. AUVs are the mobile node and do not belong to any clusters.

TABLE V
TRANSMISSION PARAMETERS

Parameters	Values
Communication Power	32 W
Electric-Acoustic Conversion Efficiency	0.5
Transmission Mode	BPSK
Transmission Rate	1500 bps
Preamble Dealy	0.5 s
Schedule Packet Size	50 Bytes
Status Packet Size	600 Bytes
Time Slot Length	7.92 s
Slot Cycle	4

environmental information such as current and channel quality. Traditional Global Network Status Obtainment (TGNSO) collects and integrates each decentralized node's local information in the following process. First, the central node broadcasts schedule packets to each buoy, and the buoys forward these packets to the surrounding SNs and AUVs to notify them to upload information. Then, SNs and AUVs upload the local information to the nearest buoy. If they are out of the communication range of the buoy, the SNs and AUVs will upload information via multi-hop transmission through the relays of other SNs. Finally, the central node collects information from the buoys to obtain the global network status.

We evaluate the time and energy consumption of one TGNSO in four scenarios. Table VI shows the test results. It can be observed that once TGNSO requires considerable time and energy, and the consumption increases with the network scale.

TABLE VI
CONSUMPTION OF ONCE TGNSO (BASELINE)

Scenario	Schedule Time	Upload Time	Total Time Consumption	Energy Consumption
a	60.96 s	121.92 s	182.88 s	8938.71 J
b	60.96 s	152.4 s	213.36 s	11141.39 J
c	91.44 s	182.88 s	274.32 s	14768.07 J
d	91.44 s	213.36 s	304.8 s	18679.55 J

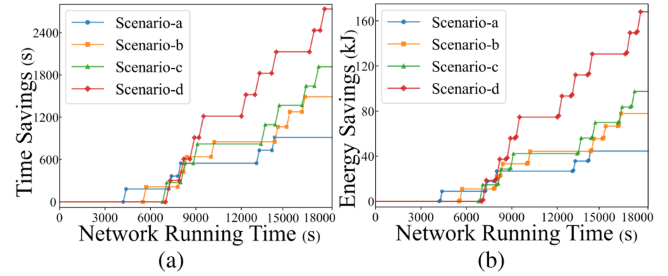


Fig. 13. The cost-efficiency gains of TNSD (proposed) over TGNSO (baseline) in four scenarios: (a) time savings; and (b) energy savings.

In addition, in order to promptly obtain global network status, it is necessary to interrupt the nodes' task execution for data upload, reducing the network performance.

To evaluate the energy saving effect of TNSD in obtaining the global network status, we conduct further additional setups for the four scenarios. We set the initial energy of each SN to a random value between 30 kJ and 100 kJ. In addition, we import ocean current data to simulate its impact on node drift. We define that it is necessary to obtain global network status for multi-task scheduling in the following cases:

- **Node Drift:** when a node drifts out of the communication range of the superior node, the communication is interrupted. The central node needs to obtain global network status to adjust the transmission power and time slot length to restore the connection of the node.
- **Energy Exhaustion:** when a node runs out of energy, it fails to send or forward data. The central node needs to obtain the global status to determine which node has run out of energy. For the data relay node, the central node schedules AUVs to replace it for data forwarding to restore communication, while no action is taken for the edge node.
- **AUV Joining:** The network topology changes when an AUV joins the cluster network as a data relay node. The central node needs to adjust the node's sending time slot sequence and routing strategy to ensure conflict-free and correct data forwarding.

We deploy TNSD in the central node, and construct the global DT at the initial stage of the network through once TGNSO process. Then the nodes periodically piggyback their local DT data in normal data packets to maintain the global DT during the network lifetime.

We evaluate the time and energy consumption of TGNSO and TNSD over the network lifetime. Fig. 13 shows the cost-efficiency gains of TNSD compared to TGNSO. It can be observed that as the network running time increases, TNSD saves

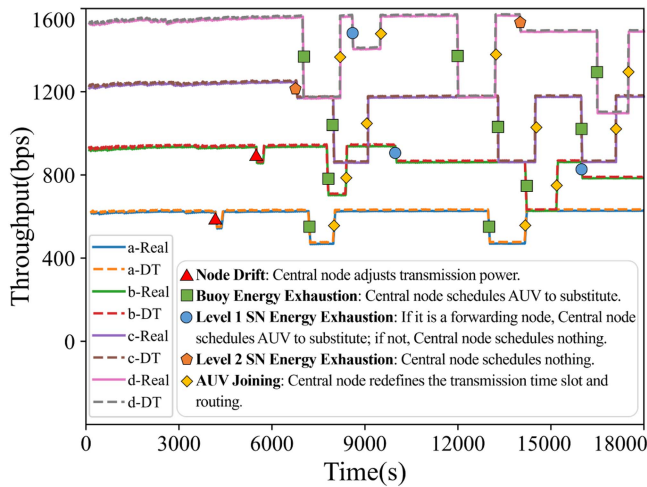


Fig. 14. Real and DT throughput comparison. Real network throughput varies by many events, and global DT realizes accurate reproduction through the high-fidelity network replica and trend prediction.

more and more time and energy. This is because TNSD can avoid the costly and frequent upload of global network status. TNSD constructs the high-fidelity network replica in global DT by piggybacking few local DT data, rapidly providing a comprehensive network status in a cost-effective way. Moreover, TNSD is more effective in saving resources for obtaining the global network status at a larger scale network. This is because the larger scale network has more nodes to upload local information, increasing the complexity of global network status obtainment, but TNSD can ignore this complexity because of avoiding the frequent TGNSO.

We also compare the real network throughput with the TNSD simulation throughput in the four scenarios. Fig. 14 shows the results. It can be observed that TNSD achieves rapid perception of network events, and the simulation throughput has a high degree of fitting with the real network throughput. This demonstrates that TNSD exhibits timeliness for event perception and accuracy for trend prediction, as well as further verifies the fidelity of global DT.

In conclusion, TNSD reduces time and energy consumption to obtain accurate and comprehensive global network status. In the four test scenarios, TNSD saves up to 2600s of time and 160kJ of energy over the whole network lifetime compared to TGNSO. Rapid and low-cost global network status obtainment benefits flexible node scheduling across multi-tasks and extending the network's lifetime.

VIII. CONCLUSION

In this paper, we present DTNA to enhance the UASNs' environmental adaptability, intelligence, and multifunctionality. Specifically, DTNA adopts a layered design to improve the DT replica fidelity and UASN control flexibility. In local DT, RAPD is designed to rapidly perceive performance variations and iteratively optimize allocation schemes, enhancing real-time environmental adaptability of resource allocation algorithms. In global DT, CMFD is proposed to accelerate AI model training

by patching scarce real data and generating extensive DT data. In addition, we design TNSD to unify demand extraction for heterogeneous tasks and rapidly provide comprehensive network status at low cost, improving the flexibility of multi-task scheduling algorithms. Extensive practical and simulation results demonstrate that DTNA accurately replicates real UASNs and effectively improves timeliness and robustness in resource allocation, reduces AI training time, and saves time and energy consumption in multi-task scheduling.

REFERENCES

- [1] I. F. Akyildiz, D. Pompili, and T. Melodia, "Underwater acoustic sensor networks: Research challenges," *Ad Hoc Netw.*, vol. 3, no. 3, pp. 257–279, 2005.
- [2] J.-H. Cui, J. Kong, M. Gerla, and S. Zhou, "The challenges of building mobile underwater wireless networks for aquatic applications," *IEEE Netw.*, vol. 20, no. 3, pp. 12–18, May/June 2006.
- [3] L. Wang, Y. Lei, B. Li, and J.-H. Cui, "Towards achieving long-lifespan and self-sustained monitoring of coastal environments," in *Proc. IEEE Int. Conf. Syst. Man Cybern.*, 2014, pp. 3413–3418.
- [4] S. Han, T. Zhang, X. Li, J. Yu, T. Zhang, and Z. Liu, "The unified task assignment for underwater data collection with multi-AUV system: A reinforced self-organizing mapping approach," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 2, pp. 1833–1846, Feb. 2024.
- [5] C. Lin, G. Han, J. Jiang, C. Li, S. B. H. Shah, and Q. Liu, "Underwater pollution tracking based on software-defined multi-tier edge computing in 6G-based underwater wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 41, no. 2, pp. 491–503, Feb. 2023.
- [6] M. Stojanovic and J. Preisig, "Underwater acoustic communication channels: Propagation models and statistical characterization," *IEEE Commun. Mag.*, vol. 47, no. 1, pp. 84–89, Jan. 2009.
- [7] M. Jahanbakhsh, W. Xiang, L. Hanzo, and M. R. Azghadi, "Internet of Underwater Things and big marine data analytics—A comprehensive survey," *IEEE Commun. Surv. Tut.*, vol. 23, no. 2, pp. 904–956, Second Quarter 2021.
- [8] C.-C. Hsu, M.-S. Kuo, C.-F. Chou, and K. C.-J. Lin, "The elimination of spatial-temporal uncertainty in underwater sensor networks," *IEEE/ACM Trans. Netw.*, vol. 21, no. 4, pp. 1229–1242, Aug. 2013.
- [9] S. Sendra, J. Lloret, J. M. Jimenez, and L. Parra, "Underwater acoustic modems," *IEEE Sensors J.*, vol. 16, no. 11, pp. 4063–4071, Jun. 2016.
- [10] Y. Gou, T. Zhang, J. Liu, T. Yang, S. Song, and J.-H. Cui, "Achieving fair-effective communications and robustness in underwater acoustic sensor networks: A semi-cooperative approach," *IEEE Trans. Mobile Comput.*, vol. 23, no. 5, pp. 5722–5739, May 2024.
- [11] Z. Wang, J. Du, C. Jiang, Z. Xia, Y. Ren, and Z. Han, "Task scheduling for distributed AUV network target hunting and searching: An energy-efficient AoI-aware DMAPPO approach," *IEEE Internet Things J.*, vol. 10, no. 9, pp. 8271–8285, May 2023.
- [12] H. Wang, Y. Li, and J. Qian, "Self-adaptive resource allocation in underwater acoustic interference channel: A reinforcement learning approach," *IEEE Internet Things J.*, vol. 7, no. 4, pp. 2816–2827, Apr. 2020.
- [13] P. A. Van Walree, "Propagation and scattering effects in underwater acoustic communication channels," *IEEE J. Ocean. Eng.*, vol. 38, no. 4, pp. 614–631, Oct. 2013.
- [14] J. Liu, X. Du, J. Cui, M. Pan, and D. Wei, "Task-oriented intelligent networking architecture for the space-air-ground-aqua integrated network," *IEEE Internet Things J.*, vol. 7, no. 6, pp. 5345–5358, Jun. 2020.
- [15] L. Li and X. Zhang, "Task allocation approach for underwater gliders in complex underwater missions," in *Proc. 4th IEEE Int. Conf. Ind. Cyber Phys. Syst.*, 2021, pp. 578–581.
- [16] S. Mihai et al., "Digital twins: A survey on enabling technologies, challenges, trends and future prospects," *IEEE Commun. Surv. Tut.*, vol. 24, no. 4, pp. 2255–2291, Fourth Quarter 2022.
- [17] E. Glaessgen and D. Stargel, "The digital twin paradigm for future NASA and US Air Force vehicles," in *Proc. 53rd AIAA/ASME/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf. 20th AIAA/ASME/AHS Adaptive Struct. Conf. 14th AIAA*, 2012, Art. no. 1818.
- [18] C. Gehrman and M. Gunnarsson, "A digital twin based industrial automation and control system security architecture," *IEEE Trans. Ind. Informat.*, vol. 16, no. 1, pp. 669–680, Jan. 2020.

- [19] T. Qiu, Z. Zhao, T. Zhang, C. Chen, and C. P. Chen, "Underwater Internet of Things in smart ocean: System architecture and open issues," *IEEE Trans. Ind. Informat.*, vol. 16, no. 7, pp. 4297–4307, Jul. 2020.
- [20] L.-T. Reiche, C. S. Gundlach, G. F. Mewes, and A. Fay, "The digital twin of a system: A structure for networks of digital twins," in *Proc. 26th IEEE Int. Conf. Emerg. Technol. Factory Automat.*, 2021, pp. 1–8.
- [21] N. Morozs, P. Mitchell, and Y. V. Zakharov, "TDA-MAC: TDMA without clock synchronization in underwater acoustic networks," *IEEE Access*, vol. 6, pp. 1091–1108, 2018.
- [22] A.-R. Cho, C. Yun, Y.-K. Lim, and Y. Choi, "Asymmetric propagation delay-aware TDMA MAC protocol for mobile underwater acoustic sensor networks," *Appl. Sci.*, vol. 8, no. 6, 2018, Art. no. 962.
- [23] Y. Noh et al., "DOTS: A propagation delay-aware opportunistic MAC protocol for mobile underwater networks," *IEEE Trans. Mobile Comput.*, vol. 13, no. 4, pp. 766–782, Apr. 2014.
- [24] J. Guo, S. Song, J. Liu, H. Chen, J.-H. Cui, and G. Han, "A hybrid NOMA-based MAC protocol for underwater acoustic networks," *IEEE/ACM Trans. Netw.*, vol. 32, no. 2, pp. 1187–1200, Apr. 2024.
- [25] S. Wang and D. Zhao, "A power control based handshake-competition MAC protocol for underwater acoustic networks," in *Proc. IEEE Int. Conf. Artif. Intell. Inf. Syst.*, 2020, pp. 665–669.
- [26] X. Ye and L. Fu, "Deep reinforcement learning based MAC protocol for underwater acoustic networks," in *Proc. 14th Int. Conf. Underwater Netw. Syst.*, 2019, pp. 1–5.
- [27] Y. Cao, W. Yu, W. Ren, and G. Chen, "An overview of recent progress in the study of distributed multi-agent coordination," *IEEE Trans. Ind. Inform.*, vol. 9, no. 1, pp. 427–438, Feb. 2013.
- [28] S. Song, J. Liu, J. Guo, B. Lin, Q. Ye, and J. Cui, "Efficient data collection scheme for multi-modal underwater sensor networks based on deep reinforcement learning," *IEEE Trans. Veh. Technol.*, vol. 72, no. 5, pp. 6558–6570, May 2023.
- [29] Z. Fang et al., "Autonomous underwater vehicle formation control and obstacle avoidance using multi-agent generative adversarial imitation learning," *Ocean Eng.*, vol. 262, 2022, Art. no. 112182.
- [30] Y.-E. Gao et al., "UVMS task-priority planning framework for underwater task goal classification optimization," *Front. Neurobot.*, vol. 16, 2022, Art. no. 982505.
- [31] I. S. Kulkarni and D. Pompili, "Task allocation for networked autonomous underwater vehicles in critical missions," *IEEE J. Sel. Areas Commun.*, vol. 28, no. 5, pp. 716–727, Jun. 2010.
- [32] P. Jia, X. Wang, and X. Shen, "Digital-twin-enabled intelligent distributed clock synchronization in Industrial IoT systems," *IEEE Internet Things J.*, vol. 8, no. 6, pp. 4548–4559, Mar. 2021.
- [33] X. Shen, J. Gao, W. Wu, M. Li, C. Zhou, and W. Zhuang, "Holistic network virtualization and pervasive network intelligence for 6G," *IEEE Commun. Surv. Tuts.*, vol. 24, no. 1, pp. 1–30, First Quarter 2022.
- [34] Y. Gong, H. Yao, X. Liu, M. Bennis, A. Nallanathan, and Z. Han, "Computation and privacy protection for satellite-ground digital twin networks," *IEEE Trans. Commun.*, vol. 72, no. 9, pp. 5532–5546, Sep. 2024.
- [35] J. Zheng et al., "Digital twin empowered heterogeneous network selection in vehicular networks with knowledge transfer," *IEEE Trans. Veh. Technol.*, vol. 71, no. 11, pp. 12154–12168, Nov. 2022.
- [36] B. Fan, Y. Wu, Z. He, Y. Chen, T. Q. Quek, and C.-Z. Xu, "Digital twin empowered mobile edge computing for intelligent vehicular lane-changing," *IEEE Netw.*, vol. 35, no. 6, pp. 194–201, Nov./Dec. 2021.
- [37] G. Shen et al., "Deep reinforcement learning for flocking motion of multi-UAV systems: Learn from a digital twin," *IEEE Internet Things J.*, vol. 9, no. 13, pp. 11141–11153, Jul. 2022.
- [38] F. A. Gers, J. Schmidhuber, and F. Cummins, "Learning to forget: Continual prediction with LSTM," *Neural Computation*, vol. 12, no. 10, pp. 2451–2471, 2000.
- [39] T. Rashid, M. Samvelyan, C. S. De Witt, G. Farquhar, J. Foerster, and S. Whiteson, "Monotonic value function factorisation for deep multi-agent reinforcement learning," *J. Mach. Learn. Res.*, vol. 21, no. 178, pp. 1–51, 2020.
- [40] R. Lowe, Y. I. Wu, A. Tamar, J. Harb, O. P. Abbeel, and I. Mordatch, "Multi-agent actor-critic for mixed cooperative-competitive environments," in *Proc. Int. Conf. Neural Inf. Process. Syst.*, 2017, pp. 6379–6390.
- [41] J. Guo, J. Liu, S. Song, C. Zhang, H. Chen, and J.-H. Cui, "Aqua-Psim: A semi-physical simulation platform based on NS3 for underwater acoustic network," in *Proc. 15th Int. Conf. Underwater Netw. Syst.*, 2021, pp. 1–5.
- [42] J. Zhu, X. Pan, J.-H. Cui, and T. Yang, "uw-WiFi: An underwater wireless sensor network for data collection and network control in real environments," in *Proc. 15th Int. Conf. Underwater Netw. Syst.*, 2021, pp. 1–8.
- [43] X. Pan et al., "RAP-MAC: A robust and adaptive pipeline MAC protocol for underwater acoustic string networks," *Remote Sens.*, vol. 16, no. 12, 2024, Art. no. 2195.
- [44] S. N. Le, Y. Zhu, Z. Peng, J.-H. Cui, and Z. Jiang, "PMAC: A real-world case study of underwater MAC," in *Proc. 8th Int. Conf. Underwater Netw. Syst.*, 2013, pp. 1–8.



Shanshan Song (Member, IEEE) received the BS and MS degrees in computer science and technology from Jilin University, Changchun, China, in 2011 and 2014, respectively, and the PhD degree in management science and engineering from Jilin University, China, in 2018. She was a post-doctoral researcher with the Department of Computer Science and Technology, Jilin University. She is currently an associate professor with the Department of Computer Science and Technology, Jilin University. Her major research focuses on underwater data collection, localization and navigation, and machine learning. She serves as the WUWNet' 2023 Publication chair.



Bingwen Huangfu received the BE degree in computer science and technology from Jilin University, Changchun, China, in 2022. He is currently working toward the PhD degree with the College of Computer Science and Technology, Jilin University. His current research interests include network architecture, resource allocation, and machine learning for underwater acoustic networks.



Jiani Guo received the BS degree in computer science and technology from Beijing Jiaotong University, Beijing, China, in 2016, and the PhD degree from Jilin University, Changchun, China, in 2024. She is currently a postdoctoral researcher with the Department of Computer Science and Technology, Jilin University. Her current research interests include MAC protocols design and performance analysis for underwater acoustic networks.



Jun Liu (Member, IEEE) received the BS degree in computer science from Wuhan University, China, in 2002, and the PhD degree in computer science and engineering from the University of Connecticut, USA, in 2013. Currently, he is a professor with the School of Electronic and Information Engineering, Beihang University, Beijing, China, also a part-time professor of the Robotics Research Center, Peng Cheng Laboratory, Shenzhen, China. His major research focuses on underwater acoustic networking, time synchronization, localization, network deployment, and also interested in operating system, cross layer design. He is a member of the IEEE Computer Society.



Junhong Cui received the BS degree in computer science from Jilin University, China, in 1995, the MS degree in computer engineering from the Chinese Academy of Sciences, China, in 1998, and the PhD degree in computer science from the University of California, Los Angeles, in 2003. She was on the faculty of the Computer Science and Engineering Department, University of Connecticut, Storrs. Currently, she is the professor of the College of Computer Science and Technology, Jilin University, Changchun, China. Her research interests include the

design, modeling, and performance evaluation of networks and distributed systems. Recently, her research mainly focuses on exploiting the spatial properties in the modeling of network topology, network mobility, and group membership, scalable and efficient communication support in overlay and peer-to-peer networks, and algorithm and protocol design in underwater sensor networks. She is actively involved in the community as an organizer, a TPC member, and a reviewer for many conferences and journals. She is a guest editor of the *ACM Mobile Computing and Communications Review* and *Elsevier Ad Hoc Networks*. She cofounded the first ACM International Workshop on UnderWater Networks (WUWNet 2006) and now serves as the WUWNet steering committee chair. She is a member of the ACM, ACM SIGCOMM, ACM SIGMOBILE, IEEE Computer Society, and IEEE Communications Society.



Xuemin (Sherman) Shen (Fellow, IEEE) received the PhD degree in electrical engineering from Rutgers University, New Brunswick, NJ, USA, in 1990. He is a University professor with the Department of Electrical and Computer Engineering, University of Waterloo, Canada. His research focuses on network resource management, wireless network security, Internet of Things, 5G and beyond, and vehicular networks. He received the “West Lake Friendship Award” from Zhejiang Province in 2023, the President’s Excellence in Research from the University

of Waterloo in 2022, the Canadian Award for Telecommunications Research from the Canadian Society of Information Theory in 2021, the R.A. Fessenden Award in 2019 from IEEE, Canada, the Award of Merit from the Federation of Chinese Canadian Professionals (Ontario) in 2019, the James Evans Avant Garde Award in 2018 from the IEEE Vehicular Technology Society, the Joseph LoCicero Award in 2015 and the Education Award in 2017 from the IEEE Communications Society (ComSoc), and the Technical Recognition Award from Wireless Communications Technical Committee in 2019 and an AHSN Technical Committee in 2013. He has also received the Excellent Graduate Supervision Award in 2006 from the University of Waterloo and the Premier’s Research Excellence Award (PREA) in 2003 from the Province of Ontario, Canada. He serves/served as the general chair for the 6G Global Conference’23, and an ACM Mobihoc’15, the Technical Program Committee chair/co-chair for IEEE Globecom’24, 16, and 07, IEEE Infocom’14, IEEE VTC’10 Fall, and the chair for the IEEE ComSoc Technical Committee on Wireless Communications. He is a registered professional engineer of Ontario, Canada, an Engineering Institute of Canada fellow, a Canadian academy of engineering fellow, a Royal Society of Canada fellow, a Chinese academy of engineering foreign member, and a distinguished lecturer of the IEEE Vehicular Technology Society and Communications Society. He is the president of the IEEE ComSoc. He was the vice president for Technical and Educational Activities, the vice president for Publications, a member-at-large on the Board of Governors, the chair of the Distinguished Lecturer Selection Committee, and a member of IEEE Fellow Selection Committee of the ComSoc. He served as the editor-in-chief of the *IEEE Internet of Things Journal*, *IEEE Network*, and *Peer-to-Peer Networking and Applications*.