Information Freshness and Resource-Efficient Scheduling in Ship–Shore Networks: An ADMM-DRL Framework

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Abstract

Maintaining real-time synchronization is a critical requirement in intelligent maritime systems, fundamentally constrained by limited satellite bandwidth and dynamic channel conditions. This paper explored a consistency-constrained resource scheduling problem in ship–shore collaborative networks, where communication delay, computation latency, and information freshness are jointly characterized using the Age of Information (AoI) metric. The problem is formulated as a mixed-integer nonlinear program (MINLP) involving tightly coupled continuous and discrete decision variables. A hybrid framework integrating ADMM with DDPG is proposed: ADMM decomposes the global MINLP into distributed subproblems, coordinating consistency via iterative dual-variable updates; DDPG agents learn adaptive scheduling policies within each continuous-action subproblem. A novel reward function grounded in the augmented Lagrangian embeds AoI constraints directly into the reinforcement learning objective. Simulations under varying sea conditions—including severe Beaufort-scale storms—demonstrate faster convergence, AoI maintenance within thresholds, and reduced satellite bandwidth consumption versus baseline methods (pure DDPG, greedy, random policies).

Keywords: Ship-shore communication, Resource scheduling, Information freshness, Age of Information (AoI), ADMM-DRL framework

1 Introduction

The rapid advancement of intelligent maritime systems has accelerated the integration of digital technologies into traditional shipping operations [1-2]. The concept of the Digital Twin (DT) has emerged as a key enabler for real-time monitoring, predictive maintenance, and intelligent decision-making in ship-shore collaborative networks, leveraging high-precision virtual mapping and dynamic simulation of physical entities [3-4]. By continuously synchronizing physical vessels with their virtual counterparts at shore-side control centers, DT-based systems offer the potential to significantly enhance operational safety, efficiency, and maintenance processes, supporting optimal decision-making for traffic scenarios and addressing challenges like data silos and delayed information flow [5-7]. For instance, DTs aid in real-time forecasting and optimization of ship power systems and provide frameworks for fault diagnosis in autonomous ships [7-8].

However, achieving reliable synchronization in maritime environments remains a challenging task [9-10]. Unlike terrestrial networks, ship-shore communication relies heavily on satellite links, which are inherently constrained by limited bandwidth, large propagation delays, and highly dynamic channel conditions [11-12]. These challenges are further exacerbated by environmental factors such as sea-state variations and vessel motion, which introduce additional uncertainty into the communication process [11-13]. As a result, maintaining timely and consistent updates between the physical system and its digital twin becomes a non-trivial problem, especially given the need for low-latency communication and computation resource allocation [14-15].

To quantify the freshness of information, the Age of Information (AoI) has been widely adopted as a key performance metric in recent studies [1, 16-19]. Compared with conventional delay-based metrics, AoI captures the timeliness of received data from the perspective of the destination, making it particularly suitable for DT synchronization scenarios [1, 13, 17, 20-23]. Minimizing AoI involves a trade-off between sending updates too infrequently (scarcity) and too frequently (congestion), which aligns with the challenge of resource management in wireless networks [20]. Nevertheless, minimizing AoI in maritime networks is fundamentally constrained by limited communication and computation resources [14, 16, 19]. Frequent updates can reduce AoI but incur excessive bandwidth consumption, while infrequent updates may lead to outdated system states and potential safety risks [16, 24-25]. This trade-off highlights the need for efficient resource scheduling strategies that jointly consider communication cost, computation delay, and information consistency [10, 14, 16, 24, 26-30].

Existing works have explored various approaches to address resource allocation and scheduling in wireless networks, including optimization-based methods and deep reinforcement learning (DRL). Optimization techniques can provide theoretically grounded solutions

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but often suffer from high computational complexity, especially in dynamic and large-scale environments such as multi-access edge computing (MEC) networks [29-30]. On the other hand, DRL-based approaches offer strong adaptability to stochastic systems and have shown promise in joint caching and power allocation in vehicular networks, as well as joint resource allocation and platoon control for UAV-hosted digital twins [3]. However, these approaches typically lack explicit mechanisms to enforce hard constraints, which may result in unstable performance or constraint violations in safety-critical applications. The inherent randomness of these problems makes identifying an optimal solution challenging [16].

To overcome these limitations, a hybrid framework that combines the Alternating Direction Method of Multipliers (ADMM) with deep reinforcement learning (DRL) is proposed for consistency-constrained resource scheduling in ship-shore networks. This approach addresses the complexity of optimizing AoI and energy efficiency by jointly considering edge association, power allocation, and digital twin deployment [16]. The key idea is to leverage ADMM to decompose the original coupled optimization problem and introduce dual variables to coordinate global consistency requirements, while employing Deep Deterministic Policy Gradient (DDPG) to learn adaptive scheduling policies in continuous action spaces. By embedding the dual variables into the learning process, the proposed approach enables effective interaction between local decision-making and global constraint enforcement, allowing for robust synchronization optimization in dynamic wireless networks [9]. This is crucial for managing real-time tasks in Digital Twin Edge Networks, where both DT update and inference tasks require timely processing [27]. Furthermore, such a framework can be applied to address issues of inaccurate synchronization in Industrial Internet of Things (IIoT) by using dual-time-scale network slicing or orchestration [26]. The integration of such robust communication and computation frameworks for digital twins over wireless networks is essential for advancing applications in domains like intelligent transportation systems and industrial automation [10, 14, 17].

The main contributions of this work can be summarized as follows:

1) A unified system model is developed for ship–shore collaborative networks, incorporating communication delay, computation latency, and AoI-based consistency constraints under dynamic maritime environments.

2) A hybrid ADMM-DRL framework is proposed to decompose the coupled optimization problem and enable distributed yet coordinated resource scheduling.

3) A novel reward design based on the augmented Lagrangian is introduced, allowing DRL agents to learn constraint-aware policies with improved stability and performance.

4) Extensive simulations demonstrate that the proposed method achieves superior convergence, robust AoI control under varying sea conditions, and significant reductions in resource consumption compared with baseline strategies.

The remainder of this paper is organized as follows. Section 2 introduces the system model and problem formulation. Section 3 presents the proposed hybrid ADMM-DRL framework. Section 4 provides simulation results and discussion. Finally, Section 5 concludes the paper and outlines future research directions.

2 System Model and Problem Formulation

2.1 Network Architecture

This study considers a hierarchical ship–shore collaborative architecture designed to support real-time data synchronization and resource management in intelligent maritime environments. The system is organized into three functional layers: the vessel-side edge layer, the maritime transmission layer, and the shore-side cloud layer. The resource scheduling scenario and communication node topology are illustrated in Figure 1; the algorithmic architecture of the proposed framework is depicted in Figure 2.

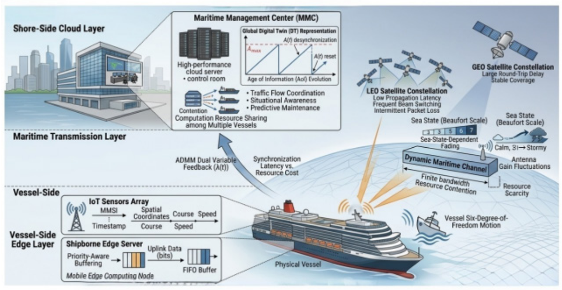

Figure 1. Scenarios and communication nodes for consistency-constrained resource scheduling

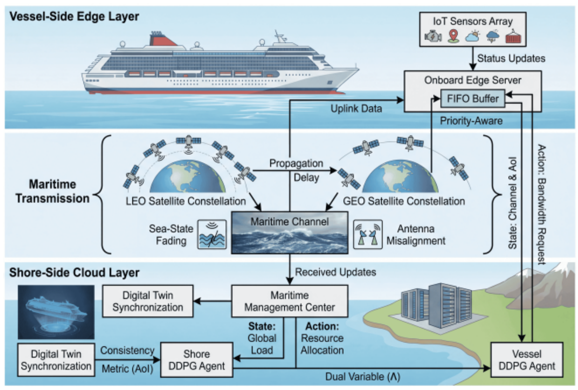

Figure 2. The architecture of the proposed Hybrid ADMM-DRL framework for consistency-constrained resource scheduling

(The diagram shows the physical layers, Digital Twin synchronization based on AoI, and the crucial ADMM dual variable (λ) feedback loop between the shore and vessel agents.)

2.1.1 Vessel-Side Edge Layer

At the vessel-side edge layer, modern large-scale commercial vessels function as mobile edge computing (MEC) nodes equipped with dense IoT sensor arrays and integrated navigation systems. The onboard edge server aggregates heterogeneous sensing data and performs preliminary preprocessing with priority-aware buffering. Given that large commercial vessels typically possess sufficient onboard power generation capacity, energy consumption is not modeled as a limiting factor in the present work. Instead, the primary bottleneck is the constrained satellite uplink bandwidth, which limits both the frequency and the volume of ship–shore data transmissions. Under these conditions, adaptive transmission scheduling is essential to prevent buffer overflow and mitigate information staleness, both of which degrade the consistency of the ship–shore information exchange.

2.1.2 Heterogeneous Maritime Transmission Layer

The maritime transmission layer is characterized by pronounced stochastic and time-varying behavior. Ship–shore communication relies on heterogeneous satellite links provided by both LEO and GEO constellations. LEO satellites generally offer lower propagation latency; however, their high orbital dynamics introduce frequent beam-switching events and intermittent packet loss. GEO satellites, by contrast, provide broader and more stable geographic coverage, yet their round-trip propagation delay—typically on the order of several hundred milliseconds—can substantially degrade latency-sensitive control and monitoring services. Furthermore, maritime wireless channels are subject to antenna gain fluctuations caused by the six-degree-of-freedom motion of the vessel, as well as signal attenuation under adverse sea states characterized by the Beaufort scale. As a result, the effective communication bandwidth varies dynamically over time, directly affecting the freshness of transmitted state information.

2.1.3 Shore-Side Cloud Layer

At the shore-side cloud layer, maritime management centers (MMCs) maintain real-time digital twin (DT) representations of vessels based on the received state updates. These digital twins support critical functions including traffic flow coordination, situational awareness, and predictive maintenance. Any delay or inconsistency in the received updates—quantified by the Age of Information (AoI)—introduces a deviation between the DT state and the physical vessel state, thereby undermining the reliability of shore-side decision-making.

Given the above system characteristics, the key challenge lies in coordinating ship-side data transmission and shore-side scheduling under bandwidth scarcity and dynamically varying communication conditions. To address this issue, this study develops a hybrid ADMM–DRL framework, where intelligent agents deployed at the ship and shore collaboratively determine transmission decisions through dual-variable coordination. Such a design aims to reduce communication overhead while maintaining high-fidelity synchronization between the physical vessel and its digital twin.

Based on this architecture, the ship–shore communication process can be formally modeled as a constrained optimization problem, where the objective is to minimize the long-term AoI of vessel state updates subject to bandwidth limitations and stochastic channel variations. In the following section, we introduce the mathematical formulation of the system model, including the maritime communication model, the shore-side computation allocation, and the rigorous mathematical evolution of the Age of Information (AoI). To support precise traffic flow coordination and situational awareness at the Maritime Management Center, the system must efficiently process critical vessel state updates—specifically focusing on variables such as MMSI, timestamp, spatial coordinates, course, and speed. By integrating these state updates with the end-to-end delay and resource cost models, we establish the foundation for our joint optimization problem. This formulation explicitly addresses the trade-off between minimizing synchronization latency and reducing satellite bandwidth consumption, ensuring that strict consistency constraints are maintained under dynamic maritime conditions.

2.2 Communication and Computation Model

To capture the dynamic behavior of the ship--shore system, we consider a discrete-time model over a finite horizon $t \in \{1,2,\ldots,T\}$, where each time slot has duration Δt. At the beginning of each slot, the vessel generates a status update packet of size $D_v(t)$ bits for synchronizing its Digital Twin (DT) at the shore-side Maritime Management Center (MMC). The communication and computation processes are jointly modeled below.

2.2.1 Maritime Communication Mode

In the vessel-side edge layer, status updates are transmitted to the MMC through a heterogeneous satellite link. Let $B(t)$ denote the transmission bandwidth allocated in time slot t. Because the maritime channel is strongly affected by sea conditions and vessel motion, its quality exhibits pronounced randomness and environmental sensitivity. To characterize this behavior, the signal-to-noise ratio (SNR) is modeled by jointly considering small-scale fading and large-scale attenuation. Specifically, small-scale fading follows a Rician distribution, which captures both line-of-sight (LoS) and non-line-of-sight (NLoS) components, whereas large-scale attenuation is represented by the sea-state-dependent coefficient $\Gamma(s)$, reflecting the degradation induced by ocean waves and vessel motion.

According to the Shannon--Hartley theorem, the achievable uplink transmission rate is expressed as

$$R(t) = B(t)\log_2\left(1+\frac{P\cdot G(t)\cdot\Gamma(s)}{\sigma^2}\right) \quad \mathbf{(1)}$$

where P is the transmit power of the onboard terminal. Since large vessels generally have sufficient onboard power supply, P is treated as a constant rather than an optimization variable. Here, $G(t)$ denotes the instantaneous channel gain and σ^2 is the additive white Gaussian noise (AWGN) power.

The corresponding transmission delay is given by

$$D_{trans}(t) = \frac{D_v(t)}{R(t)} + D_{prop} \quad (2)$$

where D_{prop} denotes the propagation delay, which depends on the satellite system. For example, it is typically on the order of tens of milliseconds for low Earth orbit (LEO) links and several hundred milliseconds for geostationary Earth orbit (GEO) links. This delay component is non-negligible and directly affects the timeliness of information delivery.

2.2.2 Shore-Side Computation Model

After the uploaded data are received, the MMC processes them to update the global DT. Although the shore-side infrastructure is equipped with high-performance cloud servers, the available computational resources must be shared among multiple vessels, which may lead to resource contention.

Let c_v denote the number of CPU cycles required to process one bit of data. If a computing resource with processing frequency $f(t)$ cycles/s is allocated, the computation delay can be written as

$$D_{comp}(t) = \frac{D_v(t)c_v}{f(t)} \quad (3)$$

This expression captures the trade-off between computational allocation and processing latency, which is essential for maintaining timely DT synchronization.

2.2.3 End-to-End Delay and Resource Cost

By combining the communication and computation stages, the total delay experienced by a status update is

$$D_{total}(t) = D_{trans}(t) + D_{comp}(t) \quad (4)$$

This end-to-end delay directly determines the freshness of received information and therefore plays a central role in the evolution of the Age of Information (AoI).

From a system perspective, the main operational cost arises from satellite bandwidth usage and shore-side computation allocation. The resource consumption in each time slot is modeled as

$$C_{res}(t) = \omega_1 B(t) + \omega_2 f(t) \quad (5)$$

where ω_1 and ω_2 are the unit costs associated with bandwidth and computational resources, respectively.

2.2.4 Age of Information (AoI) Evolution Model

To quantitatively characterize the information consistency between the physical vessel and its shore-side Digital Twin (DT), AoI is adopted as the key performance metric. Unlike conventional delay metrics, which only measure the time consumed during data transmission, AoI reflects the freshness of information from the perspective of the receiver, namely the MMC. Specifically, AoI is defined as the elapsed time since the generation of the most recently received status update.

Let $A(t)$ denote the AoI of the vessel's DT at the beginning of time slot \$t\$. To model the transmission decision, we introduce a binary variable $x(t) \in \{0, 1\}$, where $x(t) = 1$ indicates that the vessel generates and transmits a new status update in slot t, and $x(t) = 0$ indicates that no update is scheduled in order to conserve limited uplink bandwidth.

The AoI typically exhibits a sawtooth evolution over time. When transmission is scheduled, i.e., $x(t) = 1$, the generated update incurs an end-to-end delay $D_{total}(t)$, including both transmission and computation delays. After successful reception and processing at the MMC, the AoI is reset to the delay associated with that update. In contrast, when no update is scheduled, or when transmission fails because of severe channel fading, the system continues to rely on outdated information, and AoI increases linearly with the slot duration Δt.

Accordingly, the discrete-time AoI dynamics can be expressed as

$$A(t+1) = \begin{cases} D_{total}(t), \\ \text{if } x(t) = 1 \text{ and transmission succeeds.} \\ A(t) + \Delta t, \\ \text{otherwise.} \end{cases} \quad (6)$$

Since $D_{total}(t)$ depends on the stochastic maritime channel, the AoI process is a stochastic, control-dependent dynamic system.

To ensure reliable operation in intelligent maritime applications, a strict information consistency requirement must be satisfied. Let $A_{\max}$ denote the maximum tolerable AoI threshold, which may be on the order of tens of seconds for safety-critical navigation data. The system is required to satisfy

$$A(t) \le A_{\max}, \quad \forall t \in \{1, 2, \ldots, T\} \quad (7)$$

Violation of this constraint implies significant desynchronization between the DT and the physical vessel, which may compromise operational safety and decision reliability. Such violations are therefore penalized in the subsequent optimization framework.

2.2.5 Problem Formulation

Based on the communication, computation, and AoI evolution models established above, the objective is to design an effective resource scheduling policy that jointly minimizes long-term operational cost and synchronization latency while preserving strict information consistency.

To this end, we formulate a joint optimization problem over the finite horizon. The decision variables include the scheduling policy $X = \{x(t)\}$, the allocated bandwidth $B = \{B(t)\}$, and the shore-side computational resources $F = \{f(t)\}$, for all $t \in \{1,2,\ldots,T\}$. By incorporating both resource consumption and end-to-end delay, the objective is defined as a weighted sum that captures the trade-off between economic efficiency and system responsiveness:

$$\min_{X,B,F} E\left[\sum_{t=1}^{T}(\eta D_{total}(t)+(1-\eta)C_{res}(t))\right] \quad \textbf{(8)}$$

where $\eta \in [0, 1]$ is a tunable parameter that balances the relative importance of latency and resource cost.

The optimization is subject to the following constraints:

$$(C1) \quad A(t) \le A_{\max},\ \forall t \in \{1,\ldots,T\} \quad \textbf{(9)}$$

$$(C2) \quad \sum_{v=1}^{V} B_v(t) \le B_{total},\ \forall t \in \{1,\ldots,T\} \quad \textbf{(10)}$$

$$(C3) \quad 0 \le f(t) \le f_{\max},\ \forall t \in \{1,\ldots,T\} \quad \textbf{(11)}$$

$$(C4) \quad x(t) \in \{0,1\},\ \forall t \in \{1,\ldots,T\} \quad \textbf{(12)}$$

The resulting problem belongs to the class of mixed-integer nonlinear programming (MINLP) problems. Its difficulty stems from several sources. First, the binary decision variable introduces combinatorial complexity. Second, the stochastic and time-varying nature of the maritime channel induces non-convexity in both the objective function and the system dynamics. More importantly, the AoI constraint in (C1) creates strong coupling between communication delay and computation delay, further complicating the optimization.

As a result, conventional centralized optimization methods are generally unsuitable for real-time implementation because of their high computational complexity and limited scalability. This motivates the development of a more efficient solution framework. In the next section, we therefore introduce a hybrid ADMM--DRL approach that decomposes the coupled optimization problem via dual variables and enables adaptive policy learning under dynamic maritime conditions.

3 Proposed Hybrid ADMM-DRL Framework

3.1 Problem Decomposition via ADMM

The optimization problem formulated in (8) belongs to a mixed-integer nonlinear programming (MINLP) class, which is inherently difficult to solve due to strong coupling among decision variables and stochastic system dynamics. In particular, the Age of Information (AoI) constraint introduces a tight coupling between vessel-side transmission decisions and shore-side computation allocation, making centralized optimization computationally intractable for real-time ship--shore systems.

To address this challenge, we adopt the Alternating Direction Method of Multipliers (ADMM) to decompose the original problem into a set of more tractable subproblems. The key idea is to decouple the globally coupled decision variables by introducing auxiliary consensus variables, thereby enabling distributed optimization while preserving global consistency.

Specifically, we introduce a set of auxiliary variables $\mathbf{z}(t)$ to represent the shared global state associated with information freshness and resource utilization. By enforcing consistency between local decision variables and these auxiliary variables, the original optimization problem can be reformulated into a consensus form. This reformulation allows the decomposition of the global objective into separable components corresponding to the vessel side and the shore side.

Based on this transformation, the augmented Lagrangian (AL) function is constructed as

$$\mathcal{L}_\rho\left(X,B,F,\lambda\right) = \sum_{t=1}^{T}\left(\begin{array}{l}\mathcal{F}\left(x(t),B(t),f(t)\right)+\\ \lambda(t)^T\mathcal{G}\left(x(t),B(t),f(t)\right)\\ +\frac{\rho}{2}\|\mathcal{G}\left(x(t),B(t),f(t)\right)\|^2\end{array}\right) \quad \textbf{(13)}$$

where $\mathcal{F}(\cdot)$ denotes the weighted objective function that jointly captures end-to-end delay and resource cost, and $\mathcal{G}(\cdot)$ represents the set of coupling constraints derived from AoI evolution and bandwidth limitations. The vector $\lambda(t)$ denotes the Lagrange multipliers (dual variables), and $\rho > 0$ is a penalty parameter that controls the convergence behavior of the algorithm.

Under the ADMM framework, the original problem is decomposed into two iterative subproblems that can be solved in a distributed manner:

(1) Vessel-side subproblem:

Given the current dual variables \$\lambda(t)\$ and the shore-side decisions, the vessel optimizes its local decision variables, including the scheduling action $x(t)$ and the bandwidth allocation $B(t)$, by minimizing the augmented Lagrangian. This subproblem captures the trade-off between transmission delay, bandwidth usage, and AoI constraint satisfaction under dynamic channel conditions.

(2) Shore-side subproblem:

Given the updated vessel-side decisions, the MMC optimizes the computation resource allocation $f(t)$ and updates the dual variables $\lambda(t)$ accordingly. This step ensures that the global consistency constraints, particularly the AoI requirement, are enforced across the entire system.

The dual variables $\lambda(t)$ can be interpreted as dynamic consistency prices that regulate the trade-off between resource efficiency and information freshness. When the AoI approaches or exceeds the predefined threshold $A_{\max}$, the corresponding dual variables increase, thereby penalizing decisions that may further degrade information freshness. This mechanism provides an implicit coordination signal between the vessel and shore agents.

Through iterative updates of primal and dual variables, the ADMM framework enables the ship--shore system to progressively converge toward a globally consistent solution. Importantly, this distributed optimization process requires only limited information exchange between the vessel and the MMC, making it suitable for bandwidth-constrained maritime environments.

Nevertheless, due to the non-convexity of the objective function and the stochastic, time-varying nature of maritime communication channels, solving the decomposed subproblems using conventional optimization techniques remains challenging, especially in real-time scenarios. This limitation motivates the integration of Deep Reinforcement Learning (DRL) into the proposed framework. By leveraging learning-based agents, the system can approximate optimal decision policies through interaction with the environment, enabling adaptive and scalable resource scheduling under dynamic conditions.

3.2 DDPG-Based Resource Scheduling

Although the ADMM framework effectively decomposes the global optimization problem into vessel-side and shore-side subproblems, obtaining closed-form or real-time solutions remains challenging due to the stochastic maritime channel conditions and the continuous nature of the resource allocation variables. To address these limitations, we integrate Deep Deterministic Policy Gradient (DDPG) into the proposed framework, enabling adaptive decision-making in dynamic environments.

DDPG is an off-policy actor--critic algorithm that is well suited for continuous action spaces, making it particularly appropriate for bandwidth allocation and computational resource control in ship--shore collaborative networks. Within the proposed framework, each decomposed subproblem is formulated as a Markov Decision Process (MDP), defined by the tuple (S, A, R).

Taking the vessel-side agent as an example, the MDP components are defined as follows.

3.2.1 State Space

The state representation should capture both the local system dynamics and the global coordination signals. Accordingly, the vessel-side state at time slot \$t\$ is defined as:

$$s_v(t) = \{G(t), \Gamma(s), D_v(t), A(t), \lambda(t)\} \tag{14}$$

where $G(t)$ and $\Gamma(s)$ characterize the small-scale fading and the large-scale sea-state attenuation, respectively. $D_v(t)$ denotes the current data queue size, and $A(t)$ represents the instantaneous AoI. Importantly, the inclusion of the dual variable $\lambda(t)$, broadcast by the shore-side MMC, allows the agent to incorporate global consistency requirements into local decision-making. This design effectively links the distributed learning process with the ADMM coordination mechanism.

3.2.2 Action Space

Based on the observed state, the vessel-side agent determines its scheduling and transmission strategy. The action is defined as:

$$a_v(t) = \{x(t), B(t)\} \tag{15}$$

where $x(t)\in[0, 1]$ denotes a relaxed scheduling variable that is later mapped to a binary decision for practical implementation, and $B(t)\in[0, B_{total}]$ represents the allocated transmission bandwidth.

Similarly, the shore-side agent outputs the computational resource allocation $f(t)\in[0, f_{\max}]$, forming a continuous control action.

3.2.3 Reward Function and ADMM--DRL Coupling

A key challenge in conventional DRL approaches is the difficulty of enforcing strict constraints, such as the AoI requirement $A(t) \le A_{\max}$, using only environment-driven rewards. To address this issue, the reward function is designed based on the negative augmented Lagrangian, thereby embedding constraint enforcement directly into the learning process.

The immediate reward for the vessel-side agent is defined as:

$$\begin{aligned} r_v(t) \triangleq& -\left(\eta D_{trans}(t) + (1-\eta)\omega_1 B(t)\right) \\ & -\lambda(t)\Psi(t) - \frac{\rho}{2}\Psi^2(t), \end{aligned} \tag{16}$$

where

$$\Psi(t) = \max(0, A(t) - A_{\max}) \tag{17}$$

represents the violation of the AoI constraint.

This reward formulation plays a central role in the proposed hybrid framework. The first term encourages the agent to reduce transmission delay and bandwidth consumption, while the penalty terms, derived from the ADMM structure, impose increasingly strong penalties when the AoI constraint is violated. In particular, the dual variable $\lambda(t)$ acts as an adaptive penalty coefficient that reflects the current level of constraint violation.

As training progresses, the iterative update of $\lambda(t)$ provides a dynamic feedback signal, enabling the DDPG agent to learn policies that satisfy the AoI constraint while balancing system efficiency. In this way, the proposed approach avoids explicit constraint handling through centralized solvers and instead achieves distributed, learning-based optimization under dynamic maritime conditions.

3.2.4 Algorithm Execution Workflow

The execution of the proposed hybrid ADMM--DRL framework relies on coordinated interaction between global consistency enforcement and local policy learning. The overall procedure is structured as a two-timescale iterative process, consisting of an inner loop and an outer loop. In the inner loop, DDPG agents interact with the stochastic maritime environment to update their policies. In the outer loop, ADMM dual variables are updated to enforce the global AoI constraint.

At the initialization stage, both the vessel-side and shore-side agents construct their Actor and Critic networks, parameterized by θ_μ and θ_Q, respectively. Corresponding target networks and replay buffers are also established to stabilize training.

During each time slot t, both agents observe their local augmented states, which incorporate the ADMM dual variable $\lambda(t)$ broadcast by the Maritime Management Center (MMC). Based on the observed states, continuous control actions are generated by the Actor networks, with Ornstein--Uhlenbeck (OU) noise added to facilitate exploration in continuous action spaces.

After executing the joint actions, including transmission scheduling, bandwidth allocation, and computational resource assignment, the environment transitions to the next state. The AoI evolution and resource consumption are updated accordingly. The immediate reward is then computed using the negative augmented Lagrangian, which embeds both performance objectives and constraint penalties. The resulting transition tuples are stored in the replay buffer for off-policy learning.

Subsequently, the DDPG training process is performed by sampling mini-batches from the replay buffer. The Critic network is updated by minimizing the temporal-difference (TD) error, while the Actor network is optimized via the deterministic policy gradient. Target networks are softly updated to ensure training stability.

At the end of each episode, the MMC updates the ADMM dual variable using a gradient-ascent step based on the accumulated AoI constraint violation. This update provides a global coordination signal that guides subsequent policy learning toward satisfying the AoI requirement.

The complete procedure is summarized in Algorithm 1.

Algorithm 1. Hybrid ADMM–DDPG-based resource scheduling algorithm

Initialize:
• Actor networks $\mu_v(\cdot|\theta_v\mu)$ and $\mu_s(\cdot|\theta_s\mu)$ for vessel-side and shore-side agents
• Critic networks $Q_v(\cdot|\theta_v^L)$ and $Q_s(\cdot|\theta_s^L)$
• Target networks, replay buffers D_v, D_s
• ADMM dual variable $\lambda(0) = 0$, penalty parameter $\rho > 0$
For episode e = 1 to E:
Initialize environment state $s_v(0)$, $s_s(0)$
For time slot t = 1 to T:
(1) Observe states $s_v(t)$ and $s_s(t)$
(2) Select actions with OU exploration noise
(3) Execute scheduling x(t), bandwidth B(t), computation f(t)
(4) Compute AoI violation $\Psi(t) = \max(0, A(t) - A_{max})$ and reward $r_v(t)$
(5) Store transition in replay buffer D_v
(6) Update Critic by minimizing TD error; update Actor via policy gradient
(7) Soft target network update: $\theta' \leftarrow \tau\theta + (1-\tau)\theta'$
(8) ADMM Dual Update: $\lambda(t+1) = \lambda(t) + \rho\,\Psi(t)$
Output: Learned policies μ_v* and μ_s*

The computational complexity of the proposed algorithm is $\mathcal{O}(E{\cdot}T{\cdot}N)$, where N denotes the mini-batch size.

4 Simulation Results and Performance Evaluation

In this section, we evaluated the performance of the proposed hybrid ADMM-DRL framework in a sudden micro-dynamic maritime scenario under adverse sea conditions. We compared it with common algorithms including (i) Random Policy, (ii) Greedy Policy, and (iii) Pure DDPG. The specific parameters are shown in Table 1.

Table 1. Simulation parameter configuration

Parameter	Value / Distribution	Description
LEO / GEO Latency	30 ms / 600 ms	Baseline physical latency of heterogeneous satellite links
A_{max} (AoI Threshold)	15 s (Scheme A); 30 s (Scheme B)	Maximum tolerance threshold for information consistency
Vessel Count (V)	1 to 5	Number of vessels in the local sea area
Total Bandwidth (B_{total})	20 Mbps	Extremely constrained satellite bandwidth resources
Sea State (Beaufort Scale)	s ∈ [3, 7], Markov Transition	Simulate abrupt changes from calm to stormy sea conditions

The algorithm parameters for DRL & ADMM Hyper-parameters are set as shown in Table 2.

Table 2. DRL & ADMM hyperparameter configuration

Parameter	Value	Description
Actor / Critic Learning Rate	0.0001 / 0.001	Step size for neural network updates
Discount Factor γ	0.99	Discount factor for future rewards in reinforcement learning
ADMM Penalty ρ	2.0	Penalty parameter of the Alternating Direction Method of Multipliers

To ensure a fair and controlled comparison, all algorithms are tested under an identical sea-state evolution pattern derived from the Beaufort scale. In particular, a severe storm condition is enforced during the interval $t\in[80,140]$ enabling the evaluation of robustness under abrupt environmental degradation.

4.1 Learning Efficiency and Convergence Analysis

Figure 3 illustrates the cumulative episodic rewards averaged over multiple independent runs. The proposed Hybrid ADMM-DRL framework exhibits clear advantages in both convergence speed and stability. Although the learning curve shows moderate fluctuations in the early stage, the incorporation of ADMM-induced penalty terms provides structured guidance, allowing the agent to rapidly converge to a high-quality policy.

In contrast, the Pure DDPG approach also achieves convergence but suffers from noticeably larger variance, particularly during the initial and intermediate training phases. This behavior can be attributed to the absence of explicit constraint coordination, which makes it difficult to balance heterogeneous objectives such as delay minimization and bandwidth efficiency.

The Random and Greedy policies serve as non-learning baselines and thus maintain nearly constant performance throughout the training process, with significantly lower cumulative rewards. These observations indicate that the integration of ADMM not only stabilizes the learning dynamics but also improves the quality of the converged solution.

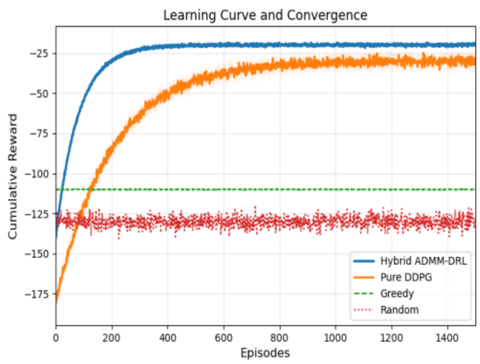

Figure 3. Convergence performance of different algorithms in terms of cumulative episodic reward

(The proposed Hybrid ADMM-DRL framework demonstrates faster convergence and improved stability compared to baseline methods.)

4.2 Micro-Tracking of AoI Evolution under Varying Sea States

To further investigate the dynamic adaptation capability, Figure 4 presents a representative AoI evolution trajectory under time-varying sea conditions. The shaded regions indicate different Beaufort sea states, with the interval $t \in [80,140]$ corresponding to severe storm conditions. The red dashed line denotes the maximum allowable AoI threshold $A_{max} = 15$ s.

The AoI evolution follows a characteristic sawtooth pattern, where successful transmissions reset the AoI, while transmission inactivity or channel degradation leads to a gradual increase. The Pure DDPG policy shows degraded performance under harsh conditions, where the peak AoI approaches the constraint boundary, indicating insufficient adaptability to rapid channel variations. In contrast, the proposed Hybrid ADMM-DRL framework demonstrates a more refined control behavior. It proactively adjusts transmission decisions and bandwidth allocation, ensuring that AoI peaks remain consistently below the predefined threshold.

This near-threshold tracking behavior reflects an efficient "just-in-time" update mechanism, which avoids unnecessary transmissions while strictly satisfying the information consistency requirement. Such behavior is particularly desirable in bandwidth-constrained maritime environments.

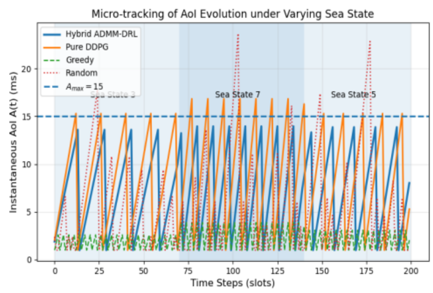

Figure 4. Micro-tracking of AoI evolution under varying sea states

(The proposed Hybrid ADMM-DRL maintains the AoI consistently below the threshold by proactively adapting transmission decisions.)

4.3 Cumulative Resource Consumption Cost

The trade-off between information consistency and resource efficiency is analyzed in Figure 5, which reports the cumulative bandwidth consumption. The Greedy policy achieves low AoI by aggressively transmitting at almost every time step, resulting in excessive bandwidth usage. The Random policy also leads to inefficient resource utilization due to its lack of scheduling intelligence.

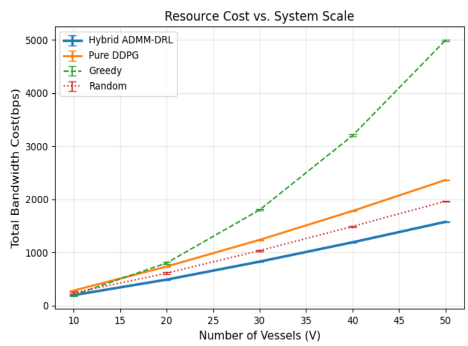

Figure 5. Total bandwidth consumption under different system scales

(The proposed Hybrid ADMM-DRL achieves the lowest resource cost and exhibits superior scalability as the number of vessels increases.)

The Pure DDPG approach significantly reduces bandwidth consumption by learning when to transmit; however, it still exhibits suboptimal allocation behavior due to the absence of global coordination. In comparison, the proposed Hybrid ADMM-DRL framework achieves the lowest resource consumption. This improvement stems from the dual-variable-driven coordination mechanism, which enables the agent to request only the minimum required bandwidth while maintaining strict AoI constraints.

These results demonstrate that the proposed method effectively balances consistency and efficiency, achieving high-quality synchronization at a substantially reduced communication cost.

4.4 Violation Rate and Generalization Robustness

To evaluate robustness under varying operational requirements, Figure 6 presents the AoI violation rate under different trade-off factors and constraint settings. The proposed Hybrid ADMM-DRL framework exhibits a consistent and monotonic decrease in violation probability as the system places greater emphasis on information freshness. This behavior confirms its ability to flexibly adapt to different operational priorities.

In contrast, the Pure DDPG method shows a higher violation rate across all settings, reflecting its limited capability in handling strict constraints without explicit coordination mechanisms. The Greedy policy maintains a near-zero violation rate, but this is achieved at the expense of excessive resource consumption, making it impractical for real-world deployment. The Random policy performs poorly, with high violation rates and weak sensitivity to system parameters.

Overall, the proposed framework demonstrates strong robustness and adaptability, maintaining low violation rates across a wide range of conditions without requiring retraining. This property is particularly important for real-world maritime systems, where operating environments and requirements can change dynamically.

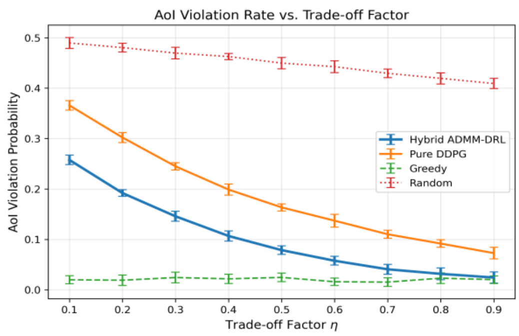

Figure 6. AoI violation probability as a function of the trade-off factor η

(The proposed Hybrid ADMM-DRL demonstrates a clear decreasing trend, indicating its ability to flexibly balance information freshness and resource efficiency.)

Summary of Comparative Analysis: Across all evaluated dimensions—including convergence behavior, dynamic AoI tracking, resource efficiency, and robustness—the proposed Hybrid ADMM-DRL framework consistently outperforms the baseline methods. By integrating ADMM-based decomposition with deep reinforcement learning, the framework achieves stable training, effective constraint enforcement, and efficient resource utilization.

5 Discussion

The simulation results provide several important insights into the design of consistency-constrained resource scheduling in intelligent ship-shore collaborative networks. From the perspective of learning dynamics, the superior convergence behavior of the proposed Hybrid ADMM-DRL framework confirms the effectiveness of integrating optimization-based decomposition with data-driven learning. Compared with conventional deep reinforcement learning (DRL) approaches, which rely solely on environmental feedback, the incorporation of Alternating Direction Method of Multipliers (ADMM) introduces structured guidance through dual variables. This mechanism effectively reshapes the reward landscape and accelerates convergence toward feasible and high-quality solutions, aligning with recent studies on constrained reinforcement learning where auxiliary optimization signals improve stability and policy robustness [9].

The micro-level Age of Information (AoI) tracking results highlight the importance of proactive adaptation in highly dynamic maritime environments. Traditional approaches, such as Pure Deep Deterministic Policy Gradient (DDPG), tend to react passively to channel degradation, which may lead to temporary violations of information consistency constraints [1, 9]. In contrast, the proposed framework demonstrates a near-threshold tracking behavior, indicating that the agent learns to anticipate adverse conditions and adjust its actions accordingly. This behavior is consistent with the working hypothesis that incorporating global consistency signals (i.e., ADMM dual variables) enables more foresighted decision-making in stochastic systems.

From a resource efficiency perspective, the results further reveal the limitations of heuristic-based policies. The Greedy strategy achieves low AoI by aggressively utilizing bandwidth resources, which leads to significant inefficiencies, especially in multi-user scenarios [17]. However, such a policy can still be competitive in relatively stable environments with abundant resources and minimal channel fluctuations, where its simplicity and responsiveness may provide acceptable performance without requiring complex learning mechanisms. This observation aligns with prior studies in communication systems, where myopic policies are often effective under static or lightly loaded conditions but fail to generalize to dynamic and resource-constrained settings.

In contrast, the proposed Hybrid ADMM-DRL framework consistently achieves a better balance between performance and cost. By leveraging the coordination capability of ADMM, the framework effectively mitigates resource contention and avoids unnecessary transmissions, resulting in significantly reduced bandwidth consumption. This demonstrates the importance of incorporating global coordination mechanisms in distributed maritime networks, where local decisions are inherently coupled through shared resources and system-wide constraints [26].

Furthermore, the sensitivity analysis with respect to the trade-off parameter η demonstrates the flexibility of the proposed approach. Unlike fixed or heuristic policies, the Hybrid ADMM-DRL framework can smoothly adapt its behavior according to different operational priorities, ranging from cost minimization to strict information freshness requirements. This adaptability is particularly valuable in real-world maritime applications, where system objectives may vary depending on mission profiles, environmental conditions, and safety requirements [2].

Despite these promising results, several limitations remain. The current model relies on simplified assumptions regarding channel dynamics and computational resource allocation, which may not fully capture the complexity of real-world maritime communication systems. In addition, the training process of DRL-based methods can still be computationally intensive, potentially limiting their deployment in resource-constrained edge environments. Future research can be extended in several directions. First, more realistic maritime channel models, including spatial-temporal correlations and satellite handover effects, can be incorporated to improve fidelity. Second, lightweight or federated learning approaches may be explored to reduce training overhead and enhance scalability. Third, extending the framework to multi-agent cooperative settings with partial observability could further improve system performance in large-scale deployments. Finally, experimental validation using real-world maritime datasets would provide stronger evidence for practical applicability.

6 Conclusions

This paper investigated the problem of resource scheduling under information consistency constraints in ship–shore collaborative networks. By explicitly incorporating the Age of Information (AoI) into the system model, the study captured the essential requirement of maintaining timely synchronization between physical vessels and their shore-side Digital Twins (DTs) under dynamic maritime conditions.

To address the resulting coupled and nonlinear optimization problem, a hybrid ADMM–DRL framework was developed. The proposed approach combines the decomposition capability of ADMM with the adaptability of deep reinforcement learning, enabling distributed decision-making while preserving global consistency requirements. In particular, the introduction of dual variables provides an effective mechanism for guiding local policies toward feasible and efficient operating points.

The simulation results demonstrate that the proposed method achieves stable learning behavior, reliable AoI control, and improved resource efficiency compared with baseline strategies. In addition, the framework can flexibly adjust its behavior according to different system priorities, thereby providing a practical balance between communication cost and information freshness.

It is worth noting that simpler heuristic strategies, such as the greedy policy, may still achieve competitive performance in relatively stable environments with sufficient resources. However, their limited adaptability restricts their applicability in realistic maritime scenarios characterized by stochastic channel variations and stringent resource constraints. In contrast, the proposed framework maintains consistent performance across varying conditions, which highlights its stronger robustness and generalization capability.

Several limitations remain. The current model is built upon simplified assumptions regarding maritime channel dynamics and computational resource allocation, which may not fully capture the complexity of practical ship–shore communication systems. Moreover, the training process of DRL-based methods can still be computationally demanding, which may limit their deployment in resource-constrained edge environments.

Future work will focus on extending the model to more realistic maritime communication environments, including satellite handover effects, spatial–temporal channel correlations, and multi-vessel interactions. In addition, lightweight learning mechanisms, such as federated or distributed learning, may be explored to reduce training overhead and improve scalability. Further investigation will also consider multi-agent cooperative settings with partial observability, as well as experimental validation using real-world maritime datasets, to strengthen the practical applicability of the proposed framework.

Author Contributions

Conceptualization, W.H. and W.L.; methodology, W.H.; software, W.H.; validation, W.H., W.L.; formal analysis, W.H.; investigation, W.L.; resources, W.H.; data curation, W.L.; writing—original draft preparation, W.H.; writing—review and editing, J.L.; visualization, W.L.; supervision, J.L.; project administration, J.L.; funding acquisition, J.L. J. L. served as the supervisor for this study. All authors have read and agreed to the published version of the manuscript.

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